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Essays on efficiency, hedging effectiveness, and volatility dynamics in cryptocurrency markets

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Abstract

This thesis contains four chapters. The first chapter introduces the background of the Bitcoin platform. The second chapter examines whether Bitcoin market is efficient by considering intra-day open, high, low and close prices. The third chapter examines the dynamic relationship between Bitcoin and Litecoin in both short run and long run by employing VARX-MGARCH-Mean model. The spillover effects are significant in both direction. For the examined time period, the covariance between Bitcoin return and the Litecoin return is not stable in the long run. The last chapter examines the hedging capability of Bitcoin and Litecoin as a cryptocurrency portfolio. Results suggest Bitcoin and Litecoin have hedging capability against some financial assets.

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Chapter 1

1.1. Introduction

For the last few years, cryptocurrencies have drawn the world's attention. Over hundreds of cryptocurrencies have been created followed by Bitcoin, such as Litecoin, Peercoin, Namecoin, Auroracoin, Primecoin, Dogecoin, Freicoin, Paycoin, Bitshares, Stellar and so on. Among these cryptocurrencies, Bitcoin is said to be the most successful cryptocurrency according to the size of its market capitalization. The price for Bitcoin has increased from nearly zero US dollars in 2009 to thirteen US dollars in 2013 and reached its peak of 1100 US dollars at the end of 2013. However, the Bitcoin price has decreased dramatically since May of 2014 to its current price of around $200 US dollars. At the beginning of both 2014 and 2015, the total market capitalization for Bitcoin was more than $10 billions US dollars and around $3 billions US dollars respectively. Even the price for Bitcoin has dropped by more than 70% over the last one year. The market capitalization for Bitcoin has always maintained more than 80% on the whole cryptocurrency market. Most of the time it occupied about 90% of the total market capitalization for cryptocurrencies.

1.1.1. First cryptocurrency

Bitcoin is the first decentralized cryptocurrency that solved the problem of double spending. One of the advantages of being decentralized is that Bitcoin user's fund could not be frozen by any authorities. Bitcoin system was practically launched by Nakamoto in 2009 and operated on a peer-to-peer network. Therefore it does not need a trusted third party to exist to make Bitcoin transaction. New Bitcoins are generated at a predetermined rate. Nakamoto (2008) suggests this rate to be every 10 minutes. Therefore it takes an hour for 6 blocks to be found. Whoever generates a block will receive some Bitcoin rewards. This Bitcoin reward was first decided to be 50 Bitcoins by Nakamoto. The generated rate is halved for every four years. Therefore it will not exceed the total number of 21 million Bitcoin in the circulation (Meiklejohn et al., 2013). Like fiat currency, Bitcoin has similar properties such as being divisible, replaceable, easy to verify, easy to transfer and impossible to counterfeit. Modern economists define money as a medium of exchange, store of value and unit of account.

1.1.2. Medium of exchange

More merchants start to accept Bitcoin as payment for various reasons. For instance, the transfer payment time is instantaneous, and all transaction is irreversible (Bohme, 2014). Like fiat currencies, Bitcoin could be used to purchase many goods and services with lower transaction fees compare to credit cards. Users are also benefited from its anonymous property. However, critics argue Bitcoin is illiquid compare to fiat currencies. Even though transaction information is sent to the entire network within few seconds, it still takes several minutes on average for a transaction to be confirmed into a block and join the blockchain. Meanwhile, the sender cannot alter unconfirmed transaction until it is confirmed to be in a block. Also, transaction fees will increase when no Bitcoins are to be generated from the network. Miners will then need transaction fees to confirm each transaction as an incentive (Derek de Vries et al., 2014). More importantly, the number of transaction per day is still significant low compare to credit card use. Most economists argue in order for the Bitcoin to be a medium of exchange, it has to achieve a critical mass so that the benefits of new Bitcoin users exceed the costs of using Bitcoin (Evans, 2014). However, Bitcoin will have to stable its price first.

1.1.3. Store of value and unit of account

Bitcoin as a store of value is very different to fiat currency. It does not have interest, but it is deflationary due to Bitcoin protocol. Bitcoin protocol defined a maximum amount of 21 million Bitcoins will be generated in total. However, the supply of Bitcoin can be changed if the open source code is changed by the developer and every Bitcoin user in the network agree to the change (Iwamura, 2014). But this will violate one of the most important properties of Bitcoin. A large amount of Bitcoin could be transferred globally at a very low cost. Critics argue governments could ban the use of cryptocurrencies because they prefer to treat with fiat currencies that could be controlled. Since Bitcoin is not backed by any authorities, it has no intrinsic value. As an open source code, many substitute cryptocurrencies could be created. The main criticism to Bitcoin as a store of value is due to its volatility. It is difficult to predict when Bitcoin price will be stable or not. The Bitcoin price between January of 2014 and January of 2015 shows a downward sloping trend, which indicates Bitcoin does not fulfil the needs of being a store of value. Due to its volatility, Bitcoin is not considered as a good unit of account.

1.1.4. Evolution of cryptocurrencies

The history of cryptocurrency could be traced back to 1982. David Chaum (1982) introduced an untraceable payment system with the feature of being anonymous for the users. In 1990, Chaum improved the system by allowing the offline transaction. Ever since then, the system has been developed along with some new features. For example, Brands (1993) proposed a similar system that allows multiple denominations and improved the double spending problem. Camenisch et al. (2006) proposed a more efficient system for storing multiple coins. However, the system could not maintain being anonymous. The main drawback for Chaum's system and its extension was that the system could be attacked by a double-spender. Therefore, these developed systems require a trusted third party as a central server. Other well-known payment systems that are also based on a central server is called e-gold and Liberty Reserve which failed to operate any more in 2009 and 2013 respectively.

In 1998, Wei Dai and Nick Szabo proposed both b-money and bit gold respectively. These two cryptocurrencies are theoretical and have never been implemented in practice, but they have similar features to Bitcoin. For example, users are represented by their public key, which keeps the feature of being anonymous. Both of them proposed the idea of the proof-of-work function that was used in Bitcoin network as well. The proof-of-work function originally came from Hashcash introduced by Adam Back in 1997 (Nakamoto, 2008).

In 2008, Nakamoto Nakamoto proposed a new cryptocurrency called Bitcoin which differed to the previous cryptocurrencies mainly in three ways: first, it is decentralized. Second, it does not require a trusted third party to exist. Third, it solves the problem of double spending without the existence of a trusted third party. At the beginning of 2009, Nakamoto released the Bitcoin source code that is an open source code and initiated the payment network. Nakamoto mined the first 50 Bitcoins on January 3 of 2009. In summary, the major difference between Bitcoin and those cryptocurrencies before Bitcoin is that trusted centralized third party was needed to verify each transaction in order to avoid unfair trading. However, the trusted third party only considered those transactions within a period of time such as at the end of each working day, which slows down the speed of transaction.

After the creation of Bitcoin, many other Altcoins and Meta-coins were created. Whereas altcoin refers to cryptocurrencies that are based on a fork of Bitcoin source code and meta-coin refers to new implementations that have different features with Bitcoin. Out of these newly created cryptocurrencies, more than 95% of them are altcoins. Over the last few years, more than 550 cryptocurrencies were created while many of them have failed to operate anymore. The cost of creating altcoins and launch them in the market is very low. All the developers need to do is to change the Bitcoin source code slightly and change the Bitcoin logo. That is the reason why hundreds of altcoins were created whereas most of them lost in the competition of cryptocurrency market. However, some of these cryptocurrencies are still successful, as developers have bought some technical innovations into these currencies. The main feature of these cryptocurrencies has in common is that they are all decentralized control and do not need a trusted third party in the system.

1.1.5. Historic events

In the early stage of Bitcoin, Bitcoin technology has mainly been used in the black market due to its special feature of anonymous. That is when it started to get media's attention. TIMES published an article on Bitcoin in April of 2011 which introduced Bitcoin to even more people. The difficulty for mining Bitcoin surpasses 100,000 from the difficulty of 1 at the very beginning. That means more people are mining Bitcoins for profit. However, in June of 2011, Bitcoin price experienced a large percentage drop in price from around 32 US dollars to 10 US dollars. The incident is known as the Great Bubble of 2011. In the same month, the largest Bitcoin exchange platform, MtGox suffered a significant breach of security and required to shut down the site for seven days. The breach leads to a leak of users tables, which contains user names, email address, and password hashes of 60,000 accounts. Followed by the security breach in MtGox, many exchange platforms were hacked or lost access to Bitcoins. For example, Bitomat was the world's third-largest Bitcoin exchange which lost 17,000 Bitcoins that belonged to their clients. MyBitcoin was hacked and lost 150,000 Bitcoins which worth over 2 million US dollars at that time. Early in 2012, the second largest Bitcoin exchange in the world, TradeHill, shut down due to operational and regulatory issues. In March of 2012, 46,000 Bitcoins were stolen from Linode due to a security breach. That is the largest theft of Bitcoin up to that date. By Bitcoin protocol, at the end of 2012, all Bitcoin rewards were halved from 50 Bitcoins to 25 Bitcoins. In 2013, there was a significant glitch in Bitcoin software causing a decrease of 23% of Bitcoin price. Later that evening, the price was recovered followed by update of software. In the same time period, a miner who updated his software created a block that is not compatible with old version of the Bitcoin software and causing a fork in Bitcoin network. The means there were two groups of miners creating and adding the block into two blockchains. Due to Bitcoin protocol, a fork is not allowed in the blockchain. The miner was asked to switch back to old version software, and the fork disappeared. In April of 2013, Bitcoin price increased to $266 compare the Bitcoin price of $13 a year before. In the same month, Bitcoin central, which was licensed as bank got hacked and resulting in a significant drop in Bitcoin price from$250 to $150. In October of 2013, FBI shut down Silk Road and seized $3.6 millions worth of Bitcoins. This results a 20% drop in Bitcoin price down to $109.71 per Bitcoin. Despite the Silk Road burst and fears over security, Bitcoin price continued to increase. By the end of 2013, Bitcoin reached 1000 US dollars for the first time. The amount of money flowing in Bitcoin network was around 245 millions US dollars which were more than the Western Union at that time. In the same time period, an online drug site called Sheep Marketplace was hacked, and 96,000 Bitcoins were stolen. The network could not do anything but watch the thief moving Bitcoin fund from wallet to wallet. Later in the same year, China central bank banned Bitcoin transaction and led to a dramatic drop in Bitcoin price. There after, the price of Bitcoin volatiles around 600 US dollars for nearly six months and then dropped significantly since the August of 2014. Up to 2015, there are 28 countries in the world that accept Bitcoin as a foreign currency. The above historic events could found from the website http://historyofBitcoin.org/.

1.2. Bitcoin

The word Bitcoin could be interpreted as the following four different meanings:

- network
- digital currency
- open source
- protocol

1.2.1. Network

1.2.1.1. Node

Bitcoin is a peer-to-peer payment network, which does not require a trusted third party to maintain the operation of the system. This peer to peer network is formed by different nodes distributed around the world. Therefore Bitcoin payment can be made anywhere in the world at a very low transaction fee across the world with instant transaction speed. Each of these nodes is represented by a PC, mobile or laptop that is using the Bitcoin software. Different nodes have different purposes in the network (Bohme, 2014). For participants who are interested in earning Bitcoin rewards, they are called miners. Their role is to verify each transaction in the network and to secure the network by preventing the existence of double spending. In return, they will receive a certain amount of Bitcoin as a reward for the work they have done. Another way to earn Bitcoin within the network is to provide either services or goods to another node. These type of nodes are known as merchants. There are also many participants running the nodes in order to collect useful information for their study. Additionally, there is a large number of nodes that are running the nodes just to manage their Bitcoin fund through a software called "wallet". Every node in the network is working independently to any governments or individual. No government or individual can control Bitcoin which means Bitcoin funds cannot be frozen or taken by any central authority.

1.2.1.2. Database

The Bitcoin network is a database that holds all transaction records and Bitcoins. All transaction records are recorded by time-stamp in a database called ledger. The ledger is distributed and maintained by nodes across the network. Therefore every node has a copy of it. A ledger contains many blocks that contain transaction records and forming a chain of blocks called block chain. By Bitcoin protocol, a new block is formed every 10 minutes followed by the latest block in the ledger known as blockchain head. All the transactions that are stored in these blocks cannot be altered unless some attackers with a huge computational power redo the proof-of-work and catch up the correct blockchain. This will be discussed later that it is not practical as Bitcoin network becomes more secured nowadays. Additionally, Bitcoin users must trust those financial institutions do not have an insider to change the database.

1.2.1.3. Public and private cryptography keys

Each node in the network has different Bitcoin address consists of a set of public key and private key, which are mathematically related. Both of these public and private cryptographic keys are made up of strings of letters and numbers, which could be generated in different smartphone devices or computers with the operation of Bitcoin open source software. Commonly the public key is referred as address, acts as an account number in banking. While the private key acts as a password for accessing the account. By Bitcoin protocol, every node can register as many addresses as they want for free. It is also recommended for each node to have more than one address for safety and privacy reason. In order to access the Bitcoins in the ledger, users will need to use their private cryptographic key (private key). In each payment, the receiver will only need to give out his/her public cryptographic key (public key) to the sender in order to receive the Bitcoin. Everybody in the Bitcoin network is sending or receiving Bitcoins anonymously by using their public keys. The network does not base on the trust of people on each other because Bitcoin has its own way of making these transactions without needing trusts to exist among people (Bohme, 2014).

1.2.1.4. Digital signature

Cryptography technology is used in each payment to secure each transaction without the existence of the trusted third party. The only information the sender needs is receiver's public key also known as the address. A digital signature is used when handling each transaction.

This method is similar to public key cryptography that was developed by Diffie, Hellman and Merkle in the 1970s (Levy, 2001). It shows a particular message (payment information) is from the signer (sender) as the digital signature cannot be replicated without signer's private key. The receiver can then take the digitally signed message (payment information) together with signer's public key to verify that particular message is from the signer (Bohme, 2014). This method effectively solves the "Man-in-the-middle" problem. Also, the signer cannot deny he/she has sent the message since only the signer has the private key.

1.2.1.5. Transaction

In order to make a transaction, every sender would need to command the input and output for that particular transaction. A node in the network would help to verify the validity of the transaction and confirm the transaction is valid. Each transaction is broadcasted in the entire Bitcoin network immediately after the transaction is created. Miners can immediately see the message is corresponding to a certain value. However, they do not know for sure that whether the Bitcoins have been spent already. Miners will trust that transaction until one block, which is known as the first confirmation. They can also wait until the second block to be made after that transaction provides them with the second confirmation. The more confirmations they have, the more secured the transaction becomes. This method can effectively avoid double spending nowadays in Bitcoin network because, in order to double spend the Bitcoins, it will cost individual/organization at least 400 million US dollars to re-mine the two blocks after that transaction which contain a large amount of proof-of-work. Therefore at zero confirmation, all the miners or recipient know the transaction message has been propagated over the entire network. After the first confirmation, all recipient and miner know it would take 400 million US dollars worth of power to fake that transaction and cost even more after second and third confirmations. According to Bitcoin protocol, it takes ten minutes for the first confirmation to appear and less time for the second confirmation. In comparison to fiat currencies, it can take a few days for VISA to verify a transaction. In this point of view, merchants tend to prefer Bitcoin network for accepting transaction as the VISA only verifies the amount of transaction and merchant does not receive the money until a few days later.

1.2.1.6. Mining

Miners are adding different transactions in a block every 10 minutes and join this new block by the blockchain head to claim the block reward. Bitcoin miners use a mathematical algorithm to generate new Bitcoin, and these newly generated Bitcoins are given as a block reward. Mining requires a certain amount of work for each block of coins. The network automatically adjusts this amount of work such that the Bitcoins are always created at a predictable and limited rate. Bitcoins are stored in the database whereas the private key that is used to access the Bitcoin in the ledger is stored in the digital wallet. When transfer Bitcoin, a digital signature is added. After a few minutes, the transaction is verified by a miner and permanently and anonymously stored in the Bitcoin network. In the network, each transaction message is broadcasted to the network so that everyone knows the transaction has been preceded (Bohme, 2014).

Block rewards for every block at the moment are 25 Bitcoins, which was halved from 50 Bitcoins. The growth rate of newly generated Bitcoins is predetermined where the rate is halved for every approximately four years. Therefore the number of new generated Bitcoins is exponentially decreased for every four years. Hence the total number of Bitcoin will not excess 21 million (Iwamura, 2014).

1.2.1.7. Wallet

The ledger in network holds the number of available Bitcoins for each address (public key). Bitcoin users will need their associated private keys to access the Bitcoin funds in the database. A Bitcoin wallet is a medium that stores a collection of private keys. It can be distributed across several devices by sharing private keys. There are many types of Bitcoin wallets, but they can be classified into the online wallet and offline wallet. Online wallet means the device is connected to the Internet and private keys could be accessed from the Internet. Offline wallets can be created using two devices, one connected to the Internet which only contains public keys and the other device contain private keys is not connected to the Internet. These devices include external storage media such as USB, external hard drive, and paper. The online wallet is more convenient while offline wallets are more secured (Dwyer, 2014).

1.2.2. Digital currency

Bitcoin is also called a digital currency. Unlike fiat currency, it is not backed up by any governments. It has value because people believe it has value and its value is purely affected by the demand and supply for it. Therefore usual monetary policy does not affect the value of Bitcoin. Also, it does not have any physical features as fiat currency. It is not made of coins or paper. It is made of a sequence of some letters. These Bitcoins can be kept on the web, computer, hard drive, mobile or other physical contents. Similar to fiat currency, each Bitcoin unit can be divided into a smaller unit. A unit of Bitcoin is equal to 100,000,000 units of Nakamotos. Another main feature for Bitcoin is that the transaction is not reversible. This feature could attract many businesses to accept Bitcoin in the payment.

1.2.3. Open source

Bitcoin is an open source software so that anyone can use it for free. Therefore any participant programmers in the network can develop the network as no one is officially in charge of development of software. Even if the creator of Bitcoin, Nakamoto Nakamoto cannot stop the operation of Bitcoin because other developers will take over. Any developers can improve the quality of open source software by checking and updating the source code. Due to this open source code feature, many altcoins were created by developers because they could modify the code to create a new cryptocurrency. To avoid confusion, a new name for this open source was given as Bitcoin core.

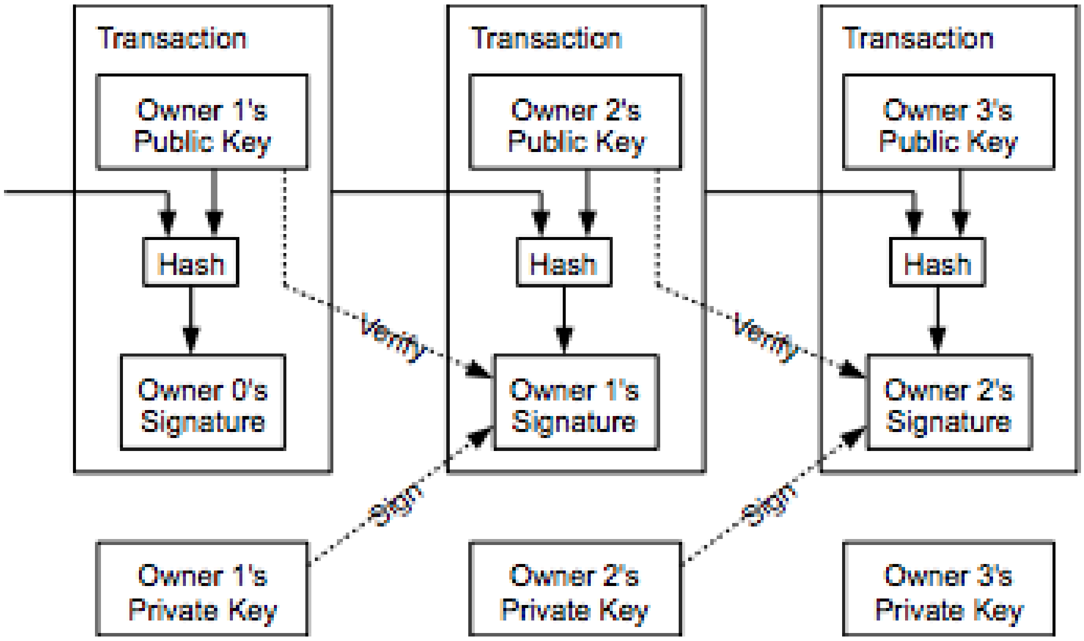
1.2.4. Protocol

Bitcoin protocol specifies the peer-to-peer network to be decentralized. Each node on the network is anonymous in a way that only public key is known to the others. It also decides the procedure for making a Bitcoin transaction. Each transaction is secured by getting a digital signature with the use of the hash function, SHA256. In order to solve the double spending problem, the protocol introduces timestamp technology in each transaction so that each generated block is provided with a created time. Miners are given newly generated Bitcoin as reward such that the network does not require a trusty third party to exist. No matter how large the computational power for the entire network is, the average time taken for each block to be generated is 10 minutes hence new Bitcoins are created every 10 minutes. This could be achieved by adjusting difficult for mining Bitcoin rewards (Nakamoto, 2008). The number of created Bitcoins is decreased exponentially because for every four years the Bitcoin reward will be halved. Given that Bitcoin core is an open source code that means anyone can change the protocol as long as the majority of the network agrees on the change (Nakamoto, 2008).

1.2.5. Technology

1.2.5.1. Transaction

In order to initiate transaction, the sender has to construct a transaction record that contains transaction information. Every Bitcoin address has an associate public key (verification key) with a corresponding private key (signing key). The first part of transaction information will include all previous transaction information for the sender. However, instead of putting transaction details in the transaction information, the sender will take the previous transaction details and use the cryptographic hash function to get corresponding output (also known as hash). Since the hash output has a fixed size, this method will simplify the digital signature process. Also, anyone in the Bitcoin network can use the cryptographic hash function to find out whether a particular transaction has more Bitcoin in input than output. This can be checked because all the transaction records are stored in the ledger by timestamp. Every transaction creates a completely different digital signature since the transaction detail is one of the inputs for the cryptographic hash function (Meiklejohn et al., 2013).



[1]

Another part of the transaction information describes the output of the transaction, which includes the amount of Bitcoin giving to the recipient and the relevant public key for the recipient as well as the digital signature for the sender. The digital signature is generated by the input of both of the transaction information message and sender's private key. With the digital signature of the transaction message and the sender's verification key, anyone in the network can verify that whether the transaction message comes from the corresponding sender. In addition, the output of that transaction information might also include how many Bitcoins is going back to the sender or how many Bitcoins are giving transaction fee for the miners. Transaction information from the sender to the recipient is then broadcasted to every node (miner) of the Bitcoin peer-to-peer network.

All miners will receive all transaction information from around the same time. Each transaction groups some input and output of the transaction, stating the amounts of Bitcoin to send and to be received by provided Bitcoin addresses. The sum amount of input in Bitcoin must be greater or equal to the output amount of Bitcoin. There is a database called unspent transaction outputs cache that only contains unspent transaction outputs. Therefore when a

[1] Source of diagram: Nakamoto (2008): Bitcoin A peer-to-peer electronic cash system

transaction is received, the inputs are checked in the unspent transaction outputs database. If all inputs are found in this database, then the transaction will be evaluated otherwise it is considered as an invalid transaction.

The first target for miners is to collate these transactions into a transaction block. The miner will then combine this group of entries into the comprehensive ledger in the Bitcoin network. Therefore each newly generated transaction block will contain a group of transactions that have been broadcast after the latest block. They do this by combining any of the two previously broadcasted transactions and use the cryptographic hash function for Bitcoin, SHA256, to transform these two inputs into a single output whereas the length of inputs can be in any arbitrage size and the size of output will need to be in exactly 256 bits length. And continue to combine a pair of these outputs into a single output at the end. This single output can effectively encode all transaction since the latest block, is then combined with the hash of the latest transaction block (Nakamoto, 2008). As this hash function takes any size of the input, it effectively avoids other people to predict the inputs. Each of the transaction blocks would be incorporated with the corresponding previous transaction block that has been accepted by the Bitcoin network. Hence forming a comprehensive global ledger in Bitcoin network, a chain of blocks. With every newly generated block, the unspent transaction output database will be updated by removing the output that has been spent. The advantage of this database is that is used very little space compare to the whole transaction database and so speed up the checking validity of new transactions. As mentioned earlier, for the sender to spend the fund, the related spending transaction must be signed with the private key for the corresponding Bitcoin address.

1.2.5.2. Blockchain

Generally speaking, Blockchain for money application is a digital ledger which could be used to record every financial transactions that have been made. However, blockchain could be applied to areas other than payment system. It could also be used to record everything including virtual assets and traditional assets in a way that everyone in the network is acknowledge the ownership of the specific asset. Once the information of an asset is being upload to the ledger, then the value of the asset will be given and could be traded in a more efficient way. The block chain in Bitcoin network was invented so that double spending will not be possible even without help from the third party. The block chain uses proof-of-work to secure the Bitcoin network. Bitcoin uses the hash function to perform proof-of-work. The hash function is an algorithm that converts an arbitrage length of data into a fixed length of the sequence of numbers and letters. Therefore a sequence of numbers will then be generated from the block chain by using a cryptographic hash function and converted into a challenge in the proof of work protocol. A good hash function must satisfy the following three properties: preimage resistance, weak collision resistance and strong collision resistance. So that it is not computationally feasible to find the input data with same hash value. SHA256 satisfies the above three properties, and that is what Bitcoin uses as the hash function (Meiklejohn et al., 2013).

1.2.5.3. Mining

The miners will take the challenge and use a mathematic algorithm to solve the challenge and come up with a separate sequence of numbers also known as the proof for the work. Using the proof of work numbers and the challenge numbers, as two inputs for the cryptographic hash function will result in a random output with a large prefix of zeros. The number of these zeros in front of some random number defines the level of difficulty for solving the challenge. If the first n bits are zeros (there are n zeros in the front), then it will take approximately 2^n trials before finding the appropriate separate sequence of number, the proof of work. According to the Bitcoin protocol, it takes on average of 10 minutes for the whole Bitcoin network to come up with the proof of work. If the technology for mining is improving or the number of miners for solving the challenge increases, then the difficulty will increase, vice versa. Follow by the boom of Bitcoin prices, the investment in Bitcoin mining equipment was estimated to be more than 200 million US dollars in 2013 (Luria and Turner, 2014).

Group mining

1.2.5.4. Timestamp

In order to solve the challenge, it requires at least one node to find the proof of work. It is possible that in the entire Bitcoin network, there are two or more nodes solve the challenge simultaneously and independently. In that case, whichever chain requires more work effort to solve will be the one accepted. This regulation will prevent the block chain forking in different directions. The node that found the proof of work will be assigned a certain amount of Bitcoins as a reward by putting the transaction into the transaction block. These certain numbers of Bitcoins are newly generated in Bitcoin system.

1.2.5.5. Wallet

Wallet software helps Bitcoin users to mange their Bitcoin funds. When a user is using his wallet software, the wallet will start to check the blockchain and show how many funds the user can access to. Then it can interface with the user by allowing the user to compute the input and output of the transaction with given Bitcoin addresses and Bitcoin value. Note that the input of the transaction must be greater or equal to the output of the transaction. The user can then use the wallet to track the confirmation status for that transaction. Then back up the wallet, as the wallet software will generate a new pair of public key and private key. To prevent other people from accessing the Bitcoin fund in the wallet, most of the private keys are encrypted with the password that is chosen by the user. In order to make the fund even saver, users store fund in multisignature outputs so that funds can only be unlocked with several signatures. Most wallets are supported by multisignature.

There are many types of wallets such as external storage media, paper wallets, hardware wallets and web wallets. Web wallets are kind of online wallets that control the fund by web and web wallet provider manages the private keys. Offline wallets include external storage media and paper wallet. Using two devices can create them, one is connecting to the Internet, and one is offline. Where the connected device only keeps the public key and the unconnected device store a collection of private keys. This will also increase the security of wallet. When making a transaction, the connected device does not have a copy of the private key. Therefore the transaction must be sent to the offline device and get signed, and then transfer it back to connected device in order to complete the transaction.

1.2.5.6. Regulation

The blockchain technology behind Bitcoin network leads to a new era of technology where decentralized platform could be built. In terms of the blockchain technology, many applications have been built to create various type of decentralized platforms along with their own cryptocurrencies. Some companies raise money by issuing these cryptocurrencies. However, as this concept is fairly new compare to other matured traditional markets. Many investors are attracted to the high return of investing these cryptocurrencies and tend to be less skeptical. Therefore, it is possible that investors are bearing high level of risk by investing these cryptocurrencies because fraud occurs due to lack of regulations. Some countries such as China and Russia, ban the initial coin offering. Since cryptocurrencies have value and investors could buy and sell them in the exchange market. Jabotinsk (2017) suggests regulations for cryptocurrency should focus on the influence it has on investors and on other financial markets. For instance, regulation of cryptocurrency should reduce the systemic risk that investors bear and protect the cryptocurrency users or customers.

1.2.5.7. Liquidity of trading platforms

Outside the cryptocurrency platform, these cryptocurrencies could be traded in different trading platforms so that cryptocurrencies could be purchased using fiat currencies or other cryptocurrencies. Different trading platforms attract different types of investors or users. For instance, British investors might use Coinfloor because it is based in London and investors could purchasing cryptocurrencies using Pound so that they do not need to purchase other fiat currency before purchasing cryptocurrencies such as Bitcoin. Some larger trading platforms allow investors to purchase cryptocurrency using different fiat currencies. For instance, Bitfinex trading platform allows investors to purchase Bitcoin using US dollar or Euro. Investors could also trade Bitcoin with other cryptocurrencies. Different platforms have different transaction fees. Some trading platforms like Coinfloor did not have transaction fee at the beginning in order to attract users to use the platform. They all have different cost for withdrawing cryptocurrencies. Some platforms take longer to accept or withdraw cryptocurrencies than others. However, one thing they have in common is that they are operated 24 hours a day and 7 days a week continuously. Some trading platforms such as Poloniex is only limited to trading among cryptocurrencies so that cryptocurrencies could not be purchased using fiat currencies.

Different trading platforms have different level of liquidity. Loi (2018) define liquidity as how easy it is for an asset to be sold in the market without influencing the price. Since most of the cryptocurrencies have limited number of supply which are generated at a predetermined rate. Some of the Bitcoin users/holders store their Bitcoin in the wallet. Some users lost their Bitcoin if they could not find their private keys. Therefore, only a portion of the Bitcoin is available to be traded in the trading platform. If one trading platform attracts more Bitcoins, then it would be difficult for other platforms to attract users to store Bitcoin in their trading platform. Therefore, it is not surprised that in the extreme time periods, the volatility for those trading platform with low liquidity tends to be larger. For instance, the bid and ask spread in Coinfloor exchange often tends to be large where the bid price and ask price are not close at all. Whereas for larger exchange platform like Bitfinex, such problem rarely happens because there are more users and the platform allows investors to short sell Bitcoin. Although this thesis does not go into details of liquidity of Bitcoin market. It should be noted that some trading platforms are not liquidity enough to handle large transaction volumes, especially when cryptocurrency markets are experiencing market turmoil. There is lack of liquidity for most of the other cryptocurrencies because their capitalization tend to be much smaller which are easily affected by large flow of capital. To the best of my knowledge, there is currently one published paper examine the liquidity of Bitcoin market. Loi (2018) use daily data between 1/Jan/2014 and 31/Dec/2015 to compare the liquidity of Bitcoin market and stock market using 5 different liquidity meausres which include Amibud's proxy for illiquidity, relative change in volume, roll, coefficient of elasticity of trading and the index of martin. Out of hundreds of Bitcoin trading exchange markets, the following five exchanges are selected to examine the liquidity of Bitcoin markets: Bitstamp, Bitfinex, BTC-e, HitBTC and itBit. Three indexs are used to proxy the stock markets including S&P small cap 600, S&P mid cap 400 and S&P 100. Out of these five liquidity measures, only Amihud's proxy for illiquidity and the index of Martin provide practical results. Results suggest Bitfinex provides the higher liquidity on Bitcoin trading. In addition, stock markets are more liquid than Bitcoin exchange markets.

1.3. Similar Platforms

A platform is known as multi-sided if the platform has more than two interdependence types of customers interacting each other (Evans, 2011). Many industries operate two-sided platforms where different platforms have different purposes and serve different types of customers. For each two-sided platform, there exist two distinct groups of customers; each group have special demand from another group. There are four types of two-sided platforms including exchange, software, media and transaction devices platforms (Evans, 2011). This section will only focus on exchange and transaction platforms. Exchange platform usually has two groups of customers known as buyers and sellers. Transaction system can be successful only if consumers are willing to purchase goods or service using particular kind of payment while the merchants are willing to accept the corresponding payment. The key feature of these two types of payment systems is their two-sidedness. In that respect, both credit card and Paypal are similar, as there exist positive network effect between two groups of users for each platform. Network effect suggests the value that users obtain from joining one side of the platform depends on the size of users on the other side of the platform.

Different types of payment methods have been created over the centuries. In the old time, people used commodities such as grain, stone to make a payment. Later on, precious metal such as gold and silver were used before governments issued some metal coins and banknotes. Payment technology has evolved from the cash-based system into electronic payment. The usage for physical payment that was used by paper check and cash is declining rapidly since consumers and businesses are adopting more convenient payment – electronic payment (Angel and McCabe, 2014).

Credit cards and Paypal are well known as electronic funds transfer and electronic payment instruments respectively. The former are physical devices that allow users to access their funds so that they can purchase at a point of sale, pay remote transaction when their cards are not present and withdraw funds from ATMs. The later is a well-known online electronic payment instrument that makes the transaction more convenient than traditional payment methods at a lower cost. Users would only need their password and email address for making a payment. None of the payers' account details will be shown to the receivers which increase security (Bohme, 2014).

1.3.1. Credit card

As a two-sided market, there exist four parties in credit card payment system including acquirer, issuer, consumer and merchant. The market has attracted many consumers and merchants on both sides of the market. The most controversial topics in this industry are the determination of interchange fee, the competition among banks, the transaction volume and the network effects within the market.

Interchange fee refers to the amount of fee that is paid by the acquirer (merchants' bank) to the issuer (consumers' bank). Rochet and Tirole (2002) investigate how interchange fee is determined when issuers' objective is to maximize profit. Under the assumption of no-surcharge rule and acquirers are competitive while issuers have market power. They have shown a change in interchange fee could affect the behaviour of both consumers and merchants. For instance, an increase in interchange fee will lead to decrease in customer fee because issuers would like to compensate cardholder in order to have higher usage of card payment. The net cost for a merchant is the difference tween merchant discount and benefits. Merchant is therefore affected by interchange fee, as the net cost for merchant will increase given that acquirers will pass the interchange fee to the merchant in order to maximize their profit. Retail prices offered by merchants to consumers might be affected by interchange fee. Gans and King (2003) have shown interchange fees do not have any effects in any degrees of competition for banks or merchants when the no-surcharge rule is applied. That means if merchants can set different prices for cash and credit card customers for purchasing any goods or service, then interchange fee will be neutral. The interchange fee is no longer neutral in the absence of no-surcharge rule and the existence of imperfect merchant competition.

The objective of credit card platform is to maximize its profit. Therefore it is important to set the right prices for both sides of the platform. Rochet and Tirole (2003) relate network economics together with multiproduct pricing and discover the determinants of price allocation between two sides of the market include platform governance, cost of multihoming for users, platform differentiation, platform's ability to use volume-based pricing, the presence of same-side externalities and platform compatibility. Rochet and Tirole first developed a basic model that could represent credit card market under the assumption that end users do not incur the fixed cost and the platform pricing is linear. They consider the case when private monopolist and Ramsey monopolist maximize profit subject to budget balance. They focus on transaction volume and derive a model when two platforms compete for the markets. Apart from fixed cost assumption, they assume consumer and merchant pay per-transaction charge instead of lump-sum fees. In a symmetric equilibrium, consumers will choose to use their credit card with lower cost while merchants will either choose to accept both high and low-cost credit cards or reject both of them. If consumers treat their credit cards as a close substitute, then merchants will pay most of the transaction charges. However, if consumers keep using the same credit card while the cost for another card is decreased then consumers will pay for the most part of the transaction charges.

Armstrong (2006) extended the work from Rochet and Tirole (2003) and considered three main factors that can affect price structure of credit card market. These three factors include types of transaction fees, network externality and the number of platforms that agents use. He considered lump sum and per-transaction fees as well as the magnitude of cross-group externalities in his three models. These models consider different degrees of market competition whereas for the competitive condition; he developed two models for both single platform and multi-platforms cases.

1.3.2. Paypal

Like Bitcoin wallet, Paypal can store money in the account and transfer money instantaneously in the world at low cost. Like credit card platform, the Paypal platform is charging one side of the platform more than another. If the transaction is being made between friends within a country, then there is no transaction fee. For international payment, the fee is between 0.5% and 2% which is still lower than using credit or debit card. However, sellers will be paying 2.9% of transaction fee for selling goods or services (Paypal). Paypal customers only need their email address and password to access their fund provided that they have already tied their bank account details to their Paypal account. In that respect, Paypal is similar to the credit card as it makes electronic transaction base on fiat money. No bank details will be revealed for each Paypal transaction which improves the privacy of users and prevents credit card fraud (Bohme, 2014). As a private company, Paypal is not ruled by banking regulation like VISA. Paypal can freeze users account and hold the money without any notice if they believe users stanch a fraud or violate their policy.

1.3.3. Private digital currency

Many private digital currencies showed up before the creation of Bitcoin. They are not supported by any governments and could be purchased with fiat currency. These digital currencies are virtual goods issued by companies. However, they have characteristics of money such as the medium of exchange, store of value and unit of account. These private digital currencies are the focus on three main industries including social networking, video games and sales of applications software (Gans and Halaburda, 2013).

Examples of social networking include Facebook credits, Amazon coins, Microsoft points and Tencent Q-coin. One thing in common for these virtual currencies is that they all use one-way exchange mechanism. Due to a large number of users, some predictions were made that these private digital currencies could be used for financial transactions like Paypal. Gans and Halaburda (2013) focus on Facebook Credit and investigate whether it is worthwhile for Facebook to change Facebook credit into full convertible so that Facebook credit can not only be purchased using fiat currency but also be able to convert back to fiat currency. They assume the objective for Facebook is to increase users activity in order to gain revenue from advertising. Given that Facebook credit can either be purchased by US dollar or earned by spending time on the platform. They conclude that Facebook would not gain any benefits for Facebook users to transfer credits to each other as well as allowing Facebook credit to exchange back to fiat currency. Peng and Niu (2009) found that it would be riskier for the platform such as Tencent to switch Q-coin into two-ways exchange mechanism rather than one-ways because the event such as liquidity crisis caused by the external impact would make platform vulnerable.

Examples of video games that issue private digital currencies include massively multiplayer online role-playing game such as Second Life and World of Warcraft (WoW). Both of these games have online players spread globally. Second Life created by Linden Lab in 2003 which allow players to create characters that represent them in the 3D virtual environment. Unlike most of the online games, players do not have goals or objectives (Mariani, 2014). The virtual world in Second Life is similar to the real world and has a similar economy. The platform plays the role of central bank in the game by issuing virtual currency called Linden dollar to the players (Mariani, 2014). Gans and Halaburda (2013) argue that it is possible for Second Life players to earn more fiat currency than they spent in the platform because Linden dollars could be earned in the game and converted into fiat currency. In that respect, Linden dollars are similar to Bitcoin currency as it allows players to create a virtual currency, to exchange for fiat currency and transfer such virtual currency to another player. However such game does not limit the amount of virtual currency that players create whereas most of Bitcoin has a maximum supply of 21 million before the year of 2140. Another type of online game WoW has similar virtual currency features except it does not allow the player to trade such virtual currency with fiat currency outside the platform. However, it does not stop the rise of the black market, as there exist players with lower wages in some countries than another (Gans and Halaburda, 2013). Kim (2013) analyzes the market efficiency for WoW through daily return price. Unlike Bitcoin, the supply and demand factors for such virtual currency depend on the game contents that could be adjusted by the platform. He also investigates whether it is possible to use such virtual currency as a method of the transaction through transaction cost. Results show it is possible when such markets are liquid. One of the big difference between these game virtual currencies and Bitcoin is that game currencies have usage value that means they still have values to the game players even they are not adopted as a method of transaction.

Chapter 2

2.1. Introduction

Different classes of assets have different purposes for investors. In general, investors who seek growth in the capital will consider stocks. Investors consider bonds as a source of income. The money market instruments are primarily for liquidity. Some investors seek for other investments such as commodities and real estate. In the recent years, cryptocurrency has been classified as a new class of assets. The year of 2017 has been a great year to hold Bitcoin for investment which has the annual return of over 1400%. Can Bitcoin be included in a portfolio of stocks? Regarding annual return, it is definitely a good asset to include into a portfolio. However, obtaining high expected return is not the only objective for some investors. The risk of including a Bitcoin should be considered. It is also important to know how Bitcoin price behaves.

Bitcoin is not like stock, bond, commodities and other traditional assets which have intrinsic value. Its value is based on the demand and supply. The price determinants of the Bitcoin price will be discussed in details in the next chapter. In this chapter, we answer the question of whether Bitcoin market is efficient. The answer to this question has some important implications; if the Bitcoin market is efficient, then investors should understand that the Bitcoin price reflects fully and correctly on all the information. In another word, no one can beat the market as the price movement follows random walk process. On the contrary, if the Bitcoin market is inefficient, then investors can seek for arbitrage opportunities based on the available information.

The cryptocurrency market started in 2009 where the first cryptocurrency, Bitcoin, has been created. Unlike traditional financial markets such as stock and bond market, where the value of stocks and bonds depend heavily on the performance of the company and the interest rates. For instance, whether the company is making enough profit as expected would affect the price of the company shares. Cryptocurrency such as Bitcoin platform does not generate any profit for providing the product (Bitcoin) or service (transaction) because it is a decentralized platform. Unlike commodity market, where most of the commodities have intrinsic values and have a variety of purposes for economic growth. Therefore, the price of some commodities depends on the business cycles. Unlike exchange rate market which depends on many aspects such as inflation rate, interest rate, current account deficits, public debt, terms of trade and political stability and economic performance. The cryptocurrency market does not have the concept of interest rate, and most of the cryptocurrencies are deflationary rather than inflationary. At the early stage of many financial markets, lots of arbitrage opportunity existed due to many reasons such as asymmetric information, immature regulation, and lack of liquidity and so on. At the early stage of Bitcoin market, the Bitcoin price had increased from less than 0.1 US dollar in 2010 to more than 1000 US dollar in 2013. The buy-and-hold rule could generate a good return for investors over this period. The Bitcoin price rapidly dropped to 200 US dollar at the beginning of 2014. After 2014, the Bitcoin market has got enough attention from the world. Therefore, relevant regulations are introduced with more people anticipating into the cryptocurrency market. Is Bitcoin market still efficient after a few years of development? This chapter examines the efficiency of Bitcoin market in the following two ways:

- Whether Bitcoin return is predictable using historical data.
- Whether arbitrage opportunity exists across different exchange markets.

The efficient market hypothesis (EMH) was first introduced by Fama (1970) which is one of the most fundamental research topics in economics and finance. Three of the most popular elements in market efficiency literature are: statistical efficiency market models, joint hypothesis testing problem and three categories of testing literature (Lee et al., 2006). This chapter focus on the last element. Most of the empirical work on the EMH can be categorized into three types. The weak form examines whether past returns are useful in predicting the future returns. The semi-strong form examines how quick the asset price responds to public information. The strong form examines whether asset price reflects on private information. None of the existing literature examines the strong form of EMH in Bitcoin market. Some studies examine the semi-strong form by considering public information events and examine the speed of price adjustment to a particular event. Most of the Bitcoin-related literature examines the weak form efficiency market hypothesis. One of the most popular approaches is to examine whether there exist statistically significant autocorrelation in the asset returns using serial correlation tests. If there exist a pattern of autocorrelation in the assets returns, then the market is interpreted as inefficient. However, such pattern is likely to disappear once it is being discovered by the market participants. Another method is to consider a long run relationship between any two assets. If the relationship is stable in the long run, then the price movement of another asset could be useful to examine the price movement of the examined asset. One of the most frequent use approaches is the cointegration relationship, where the prices of two assets are not stationary but the linear relationship of the prices for these two assets are stationary. Although the findings are mixed regarding Bitcoin market efficiency, the majority of the findings suggest Bitcoin market is inefficient. The details of this literature will be discussed in the literature review section.

This chapter focuses on the weak form of the efficient market hypothesis testing by breaking this hypothesis into two subcategories. First, we test whether historical price/returns information is useful in predicting the current Bitcoin return. Given that the Bitcoin exchange markets are trading continuously 24-hours-a-day and 7-days-a-week. The open, high and low prices are considered in addition to the close price in order to test for the efficient market hypothesis. Moreover, the historical range-based volatility estimator has been used to predict both the current conditional return and the current conditional variance. Moreover, the Granger causality test is being used to examine whether the returns of another cryptocurrency asset, Litecoin, is useful is predicting the current Bitcoin returns. Secondly, the arbitrage opportunity is being investigated across 5 US dollar based Bitcoin exchange markets. Results from these two subcategories suggest the Bitcoin market is not efficient in the short run. Also, the past close price returns do not provide much information of the current return. The historical intraday-extreme data contains useful information in predicting the current Bitcoin return. There exist other tests for examining the weak form of market efficiency hypothesis via examining the law of one price, anomalies and autocorrelations. Similar studies examine the Bitcoin market efficiency using these tests which will be discussed in details in the following 2.2 literature review section.

To the best of my knowledge, only one study considers the intra-day high and low prices when investigating the efficient market hypothesis. Pieters and Vivanco (2017) examine the law of one price for Bitcoin markets by investigating the price differences in 11 different Bitcoin exchange markets. The vector error correction model with the vector of the Bitcoin prices is considered to examine the long run relationship. Different types of price are considered for analysis including the weighted average price, intra-day high price and intra-day low price. Results indicate most of the exchange market follows the law of one price where the Bitcoin price of one exchange market is cointegrated with the Bitcoin price in another exchange market. However, in this chapter, the intra-day open, high, low and close prices will be used to calculate the corresponding returns and investigate the return predictability within one exchange market and the arbitrage opportunities across exchange markets in the short run. Also, this is the first study to consider historical range-based volatility estimator in examining the Bitcoin market efficiency. Results suggest intra-day extreme data provide useful information on return predictability.

The rest of this chapter is organized in the following way: section 2 provides the literature review on the efficiency of the Bitcoin market follows by the research questions. Sections 3 and 4 describe the methodology and data that will be used for this chapter respectively. Section 5 interprets the estimated results and discuss the hypotheses that are raised in section 2. The conclusion is drawn in section 6.

2.2. Literature review

2.2.1. MARKET EFFICIENCY

The section provides existing studies on examining the hypothesis of an efficient market for Bitcoin. Different models are employed to examine the weak form of market efficiency. The most popular method is to use cointegration methodology where the Bitcoin price of one exchange market has a linear relationship with another Bitcoin price from another exchange market or with the price of traditional assets in the long run. Moreover, the behaviour of Bitcoin price (return) is being examined by using a variety of tests including Ljung-Box test, Runs test, Bartel's test, variance ratio test, BDS test and rescaled Hurst exponent for long memory test. These tests are used to examine whether the Bitcoin price (return) follows random walk process. Although there exist evidence that Bitcoin market follows the efficient market hypothesis, most of the studies suggest Bitcoin market violates the efficient market hypothesis.

Alam et al., (2017) employ AR(1)-GARCH(1,1) model and apply the unit root test with two endogenous structural breaks to examine the weak form of efficient market in cryptocurrency. Daily prices for both Bitcoin and Litecoin are collected for the period between 10/April/2015 to 10/April/2016. The structural breaks for Bitcoin and Litecoin markets are 2/November/2015 and 16/June/2015 respectively. The log return of average daily price for both Bitcoin and Litecoin are used as the endogenous variables in two univariate models. Six unit root tests including augmented Dickey-Fuller test, dickey fuller generalize least square test, Philips perron, Kwiatkowski Phillips Schmidt Shin, Elliot Rothenberg stock point optimal and ng Phillips tests. Results indicate there exist unit root in the Bitcoin model while Litecoin model shows opposite results suggesting Litecoin market has a weak form efficient market.

Naidu (2016) tries to identify whether the law of one price for Bitcoin holds by investigating the Bitcoin closing daily prices in 4 South African exchange, 48 USD denominated exchanges, 32 Euro denominated exchanges and 14 GBP denominated exchanges. Two sets of the sample are being tested where both samples are range between the periods of 19/May/2014 and 30/October/2015. Both sample sets use ordinary least squares regressions to examine whether there exist cointegration relationships among these Bitcoin prices. The first sample set compares the Bitcoin prices denominated in South African currency, ZAR, against the GBP, EUR and USD. In this sample set, the Bitcoin users are offering and bidding on the same platform at Localbitcoin.com. The second sample set compares the Bitcoin prices in different exchange markets including BitX, HitBTC and Coinfloor. In this sample set, the Bitcoin prices are controlled by the exchanges. Two cointegration tests are employed for two sample sets. Results suggest there exist three cointegrating relations among the ZAR, GBP, EUR and USD exchanges. For the second sample set, the results suggest only one cointegration relation could be found among BitX, HitBTCUSD, HitBTCEuro and Coinfloor GBP exchanges. Therefore, some of the Bitcoin prices among different exchanges are found to be moving together in the long run. Therefore the law of one price theory holds in this study.

Healy (2014) examines the momentum anomaly in the Bitcoin market using daily Bitcoin returns between 23/July/2010 and 06/March/2013 to examine whether Bitcoin market is in weak form efficiency. Data was collected from MtGox exchange which has shut down already. Two OLS regressions are estimated with Bitcoin returns as the dependent variables and daily prices for oil, gold and silver as independent variables as well as another control variable called New posts which represent the number of posts of Bitcoin posted in BitcoinTalk every day. To examine the momentum feature of the estimated model, each of the estimated regression includes a set of dummy variables where the significance of dummy variables indicating the existence of momentum feature. The first regression (second regression) is expected to have positive (negative) coefficients on the dummy variables if the rise of the prices in the previous period is followed by the price rise (fall) on the current period. The following displays both of the regressions using dummy variable analysis:

$$R_{bt} = C_0 + \delta x_1 + \delta x_2 + \delta x_3 + \delta x_4 + \delta x_5 + \beta_1 Gold + \beta_2 Oil + \beta_3 Silver + \beta_4 Newposts + e_t \quad \text{Equation 2.2.1.1}$$

$$R_{bt} = C_0 + \delta z_1 + \delta z_2 + \delta z_3 + \delta z_4 + \delta z_5 + \beta_1 Gold + \beta_2 Oil + \beta_3 Silver + \beta_4 Newposts + e_t \quad \text{Equation 2.2.1.2}$$

Where R_{bt}, Gold, Oil, Silver represent the Bitcoin return, gold price, oil price and silver price respectively. Note that Bitcoin return is calculated using daily Bitcoin closing price, BTC, with $R_{bt} = \ln(\frac{BTC_t}{BTC_{t-1}})$. The x_i and z_j variables indicate the positive and negative returns for i and j previous periods respectively with i and j=1,2,3,4,5. To examine whether Bitcoin returns follow a random walk, Healy (2014) employs ADF unit root test, Runs test and autoregressive test. Results indicate there exists a significant relationship between the current Bitcoin returns and positive price changes from the previous period. Also, evidence against the weak form efficient market hypothesis could be found from ADF test and Runs test results. Therefore, Bitcoin market is weak efficient.

Kurihara and Fukushima (2017) update the data to the range between 17/July/2010 and 29/December/2016 and examine the anomaly in the Bitcoin market. Adding to the OLS regression, the robust least squares estimation is employed which avoids the problem of outlier when using standard OLS estimation. Kurihara and Fukushima examine the day-of-the-week effect by including 7 dummy variables, d_k where k=1, …, 7, into the following regression which represent Sunday, Monday, Tuesday, Wednesday, Thursday, Friday and Saturday.

$$R_{bt} = C_0 + \gamma d_1 + \gamma d_2 + \gamma d_3 + \gamma d_4 + \gamma d_5 + \gamma d_6 + \gamma d_7 + \varepsilon_t \qquad \text{Equation 2.2.1.3}$$

Results suggest the weak form efficient of Bitcoin market is rejected as the null hypothesis of randomness is rejected.

Fink and Johann (2014) examine the price formation of Bitcoin and whether Bitcoin price is efficient. Instead of daily data, the one-minute price data for Bitcoin is collected for examining whether Bitcoin price is efficient. A set of tests are used to examine the randomness of Bitcoin price including Jarque-Bera test, Runs test, Portmanteau test and variance ration test. Results suggest Bitcoin price is not efficient. Also, the vector error correction model (VECM) with four lags is estimated using the Bitcoin price among different exchanges including MtGox(USD), MtGox(EUR), BTCn(CNY), BTCe(EUR) and Bitstamp(USD). Two samples periods are examined, the first period is between 13/September/2013 and 25/February/2014. The second period is between 25/February/2014 and 22/May/2014. The results of the VECM suggests Bitcoin prices among different exchanges are cointegrated.

Bariviera (2017) examines the long memory of Bitcoin returns and volatility between 18/August/2011 and 15/February/2017. Logarithmic return of Bitcoin is calculated in the same way as R_{bt}. The daily price volatility is calculated by taking the logarithmic difference between intraday highest and lower prices. The Hurst exponent is computed by two different methods including the rescaled range method and de-trended fluctuation analysis (DFA) method. For the DFA method, two sub samples are examined in addition to the whole sample. The first sub-sample is between 18/August/2011 and 31/December/213 where the second sub sample is between 1/January/2014 and 15/February/2017. Results suggest there exist essential persistent in daily Bitcoin returns for the first sub sample period. The daily volatility exhibits stronger long memory than daily returns of Bitcoin.

On the contrary, the following study suggests Bitcoin follows the hypothesis of efficient market. Bartos (2015) collects three types of data to examine whether Bitcoin price follows efficient market hypothesis. The aggregate Bitcoin price index from different exchanges is collected for the period between 4/March/2013 and 31/July/2014. The second type of data is the daily prices for financial instruments such as Gold, S&P 500, Dow Jones, Google stock price and Facebook stock price for the same sample period. The third type of data is the Wikipedia view which is used to represent the demand for Bitcoin. All of these variables are first logarithmic differenced so that stationary variables are examined. The OLS estimation is used to examine the linear relationship between the Bitcoin price and the financial variables. Error correction model is used to examine the long run trend. Results indicate no trend could be found in the long run and the dependent variables which are used to explain the Bitcoin price do not have any effect on explaining the Bitcoin price in the long run. Moreover, this paper examines the effect of public announcements on the Bitcoin price by using error correction model where the results indicate Bitcoin price reacts to public announced information which follows the efficient market hypothesis.

The following studies show mixed evidence in examining the efficiency of Bitcoin market. Urquhart (2016) examines the efficiency of Bitcoin market by employing six different tests on the Bitcoin returns including the Ljung-Box test, Runs test, Bartel's test, variance ratio test, BDS test and rescaled Hurst exponent for long memory test. These tests are used to examine the autocorrelation, independence, random walk hypothesis and the independently identically distribution of Bitcoin returns. The Bitcoin return is defined in the same way as R_{bt}, where the closing price for Bitcoin is collected between 1/August/2010 and 31/July/2016. Three different periods are examined in this study including the whole sample and two sub samples periods. The first sub sample is range between 1/August/2010 and 31/July/2013. The second sub sample is from 01/August/2013 and 31/July/2016. Results suggest Bitcoin market is not weak efficient over the whole sample period but becomes efficient in the second sub sample period. Nadarajah and Chu (2016) use the same data as in Urquhart (2016) where the Bitcoin price is collected between 1/August/2010 and 31/July/2016. As in Urquhart (2016), Nadarajah and Chu consider the same three periods. Instead of using R_{bt} as the dependent variable, Nadarajah and Chu propose to use R_{bt}^{m} where m=17. In addition to the tests that are used in Urquhart's paper, Nadarajah and Chu also employ the wild-bootstrapped automatic variance ratio test, spectral shape test, robustified portmanteau test and generalized spectral test which are used to examine the random walk hypothesis, existence of seral correlation and the martingale different hypothesis. Results suggest Bitcoin market is weak efficient for all examined sample periods.

Quijano (2017) employs both cointegration and event study methods to examine whether Bitcoin market is efficient. The daily Bitcoin prices are collected from 52 different exchanges between 1/December/2014 and 21/August/2016. Results suggest there exist linear relationship of Bitcoin price among exchanges. Quijano follows the same procedures as in Stark and Wellenstam (2015) who examine the effect of a single event, the opening of Coinbase Bitcoin exchange platform, which is found to be statistically significant. The procedures for examining the even study is contributed by Campbell et al. (1993) and MacKinlay (1997), which covers the following 5 aspects event definition, event window analysis, abnormal returns, statistical tests and conclusion. Different to Stark and Swellendam, multiple events have been examined. In total, 17 events are included such as Cyprus government accept citizen to use Bitcoin; China prohibits the use of Bitcoin and so on. Both good and bad news is included in the analysis. Results suggest 12 out of 17 events are found to be statistically identified that the announcements of each event have significant impact on Bitcoin price. Results indicate law of one price holds in Bitcoin market.

2.2.2. Historical volatility

This section shows most of the existing studies suggest range data should be considered when for volatility estimation which would provide more accurate and efficient estimation than traditional models such as ARCH and GARCH models. It has been shown by many studies that volatility is useful in predicting the future movement in finance market. Most of the existing studies use close price to calculate the price return and use the return variance as the proxy of volatility. Both ARCH and GARCH models are widely used for volatility modelling and forecasting. Many extensions are developed for different purposes. However, it has been shown by many studies that using the range data which involves high, low, close and open prices will increase the performance of volatility estimation. The history of using range data to estimate the volatility could be traced back to 1980 where Parkinson uses both high and low prices to model the historical volatility. Garman-Klass (1980) extends Parkinson's method by including both open and close prices which were the first methodology to involve all high, low, close and open prices in estimating the historical volatility. Later on, the method to estimate the historical volatility using range data has been developed by Rogers-Satchell (1991) and Yang-Zhang (2000), which will be discussed in details in the methodology section.

Shu and Zhang (2005) examine the performance of the above four historical volatility estimators by using the S&P 500 index return data. It is shown that if stock price follows random walk process with a drift and no opening jump, then each of these four range estimators provides good estimation of the true variance. If the magnitude of the drift term varies significantly, then the Parkinson estimator and Garman and Klass estimator will overestimate the variance, whereas the other two range estimators are independent of the value of drift terms. If the magnitude of the opening jump is large, then only Yang Zhang volatility can provide an accurate estimation of the variance. If volatility is time-varying instead of being constant, then the estimation error tends to be smaller on average. Overall, the results indicate range estimators are useful in capturing the short-term dynamics of volatility.

Alizaded et al. (2002) use the range-based models to performance volatility dynamic analysis in 5 U.S. dollar exchange rates. Results show the range-based models are more efficient than traditional volatility models in volatility or risk modelling. Chou (2005) proposed a range-based model called conditional autoregressive range (CARR) model for forecasting the volatilities. Results suggest CARR model provides shaper estimates for volatility which is more efficient than GARCH model. Also, the CARR model has been extended to CARRX where the X represents the exogenous variables which could be included in forecasting the volatility. In line with Chou (2005), Brandt and Diebold (2006) suggest the GARCH models do not always provide accurate estimation in certain applications, who considered the range-based models on various financial markets provide efficient volatility estimator. Martens and van Dijk (2007) suggest range volatility estimators are especially useful in continous trading model, which provides 5 times more efficient than traditional model of volatility estimation.

Although many studies suggest range data could provide more accurate volatility estimator than traditional models. There are some studies which suggest range data do not help to predict the returns. For instance, Schwert (1990) shows range data is useful in predicting the volatility but not stock returns.

Molnar (2012) modify the traditional GARCH model and use the range data to develop a range GARCH (RGARCH) model. Molnar argues that GARCH model should only consider as filter instead of using it estimate the volatility. Results indicate the RGARCH model performs better than GARCH model in both in-sample fit and out-of-sample forecasting.

2.3. Research questions

Extend the following two research questions:

- Whether Bitcoin return is predictable using historical data.
- Whether arbitrage opportunity exists across different exchange markets.

This section talks in details how these two research questions could be answered in several sub-questions. One of the differences between cryptocurrency exchange market and the traditional financial exchange market is that all cryptocurrency exchange markets are operating 24 hours a day and 7 days a week globally. To the best of my knowledge, all the relevant Bitcoin papers use close price to represent the price of the day and calculate the Bitcoin price return using close price in the same way as other papers which examine the traditional financial markets. However, being operating worldwide continuously, such method might lead to loss of useful information. Note that the close price in many exchange markets is recorded at around 23:45 in order to differentiate from the open price at 00:00, hence the close price is not even practically the end of the day. The coordinated universal time is used to indicate the time because it is the primary time standard by which the world regulates the time. Although intra-day high and low prices might overestimate and underestimate the Bitcoin price on that day. Both close and open prices are just representation at that particular minute. Hence close price does not have any special meaning when compared to open, high and low prices. Therefore it is interesting to examine whether the intra-day extreme prices behave differently to the open and close prices? Are intra-day high and low prices useful in predicting the Bitcoin price movement? In order to answer these questions, each of open, high, low and close prices will be used to calculate the Bitcoin return for analysis. Also, does the past return of another cryptocurrency, Litecoin, has significant effect in predicting the Bitcoin return?

The following three hypotheses are set to answer the above questions:

1. Bitcoin returns that are calculated by open, high, low and close prices lead to the same conclusion regarding efficiency for the Bitcoin market
2. The past Bitcoin returns that are calculated using intra-day data are significant in predicting the current Bitcoin returns
3. The lag of returns of another cryptocurrency, Litecoin, Granger causes the current Bitcoin return.

It is interesting to examine the first point above because no research has been done to examine whether these prices behave differently. Regarding the third point above, it is interesting to examine Litecoin because Litecoin acts as a payment system share many features as Bitcoin. However, it is different to Bitcoin in many ways. The following table shows the main feature of both Bitcoin and Litecoin.

	Bitcoin	Litecoin
Both are decentralized	First cryptocurrency using the blockchain technology	Use the idea of blochain technology from Bitcoin
Both use proof of work	SHA256: First to introduce SHA256 mining algorithm	Scrypt: First to introduce scrypt mining algorithm which is more efficient than SHA256
Total supply	21 million coins	84 million coins
How many blocks until halving	210,000 blocks	840,000 blocks
Confirmation time for each block	Average 3 minutes for each block	Average 10 minutes for each block

Table 2.3.1: Comparison of Bitcoin and Litecoin features

Although Bitcoin shares some properties as fiat currency where it could be used for trading as a medium of exchange to purchasing goods or services. Its volatility is more like a financial asset rather than fiat currency. This chapter also examines whether historical data is useful in predicting the future volatility. Moreover, is the historical data based volatility estimator useful in predicting the Bitcoin return? The following two hypotheses are set to answer these questions:

4. Historical data-based volatility estimator is significant in predicting future Bitcoin return volatility
5. The past Bitcoin return volatility is significant in predicting the Bitcoin return.

In order to answer the second part of the research questions, this chapter examines the arbitrage opportunity by investigating whether the returns across different exchange markets are significantly different. The last hypothesis is set to the following:

6. Bitcoin returns across different exchange markets are significantly different. In another word, arbitrage opportunity does not exist.

2.4. Methodology

This section is divided into two sub-sections which introduce the methodology that will be employed for the return predictability and the arbitrage opportunity testing. The first section uses an autoregressive (AR) model as well as the AR model with exogenous variables as the conditional mean equations. The second section uses ordinary least square regression. Both sections use traditional generalized autoregressive conditional heteroscedasticity (GARCH) model and exponential GARCH model as conditional variance equations. Also, the first section uses GARCH-in-mean model and the EGARCH-in-mean model to examine whether the conditional variance is significant in predicting the current returns. Moreover, the historical range-data will be considered in above mentioned conditional variance equations and form the range-based GARCH type of models when examining the return predictability. The autoregressive conditional heteroskedacity (ARCH) model solves the heteroscedasticity phenomena. However, if the volatility do not happen at particular times. In another word, if the time for volatility to happen is stochastic. Then generalized ARCH model is helpful.

2.4.1. Return predictability

The autoregressive model of order p denoted as AR(p) is defined as the following:

$$R_t = c + \sum_{i=1}^{p} \lambda_i R_{t-1} + \varepsilon_t$$
$$\{\varepsilon_t | \phi_t\} \sim N(0, \sigma_t^2)$$

Equation 2.4.1.1

Where R_t represents the Bitcoin return at time t, $\lambda_1, \dots \lambda_p$ are the parameters of the model, c represents the constant term, ε_t is a white noise process with zero mean and variance σ_t^2.

The autoregressive model with exogenous variable is the same model as above along with the additional variables shown as the following:

$$R_t = c + \sum_{i=1}^{p} \lambda_i R_{t-1} + \tau_1 r_{t-1} + \varepsilon_t$$
$$\{\varepsilon_t | \phi_t\} \sim N(0, \sigma_t^2)$$

Equation 2.4.1.2

Where r_{t-1} represents the return calculated using other price series data, τ_1 represents the parameter of variable r_{t-1}.

2.4.2. Measures of historical volatility

Close-to-close (C), Exponentially weighted (C)

There are many ways to measure historical volatility. The most common method was using close prices to calculate log return in order to calculate the volatility. This method is called close-to-close volatility which works the best compared to other methods given the sample size is large.

The formula for the annualized close-close estimator (Parkinson, 1980) is given as below:

$$volatility_{close\ to\ close} = \sigma_{cc}$$
$$= \sqrt{\frac{F}{N-1}} \sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2} = \sqrt{\frac{F}{N-1}} \sqrt{\sum_{i=1}^{N} Ln(\frac{C_I}{C_{i-1}})}$$

Equation 2.4.2.3

For a series of closing prices (c_1, c_2, c_3, … , c_i), which are quoted at equal interval of units of time. X_i equals to $\ln(c_i/(c_{i-1}))$. As the mean rate of return, $\overline{x}$ is zero. F represents the number of annual trading days.

An alternative method that uses close price is called exponentially weighted volatility, which has an advantage if there was a spike in volatility, as it will gradually decrease to a lower level instead of having disappearance suddenly in historical volatility. However, this method is still rarely used because it does not handle regular volatility driving events very well. The most criticized disadvantage of using closing price only is that this method might lose much useful information from high, low and open prices. Therefore reduce the efficiency of estimating volatility.

Parkinson (HL), Garmen-Klass (OHLC), Rogers-Satchell (OHLC)

In order to get better estimation in calculating volatility, some or all of the open, close, high, low prices are used. First advanced volatility estimator was created by Parkinson (1980) by using high and low prices. The assumption of continuous trading in this method underestimates the volatility. The following shows the Parkinson estimator:

$$volatility_{parkinson}=\sigma_p=\sqrt{\frac{F}{N}}\sqrt{\frac{1}{4Ln(2)}\sum_{i=1}^{N}(Ln(\frac{h_i}{l_i})^2} \quad \text{Equation 2.4.2.4}$$

where h_i and l_i represents the high and low prices during a trading day respectively.

The first developed model extended from Parkinson is called Garman-Klass volatility estimator (Garman and Klass, 1980). This method has much higher efficiency than Parkinson model as it involves open and close prices as well. However, it does not solve the problem of overnight jumps hence underestimates the volatility. In addition, all these measurements assume average return to be zero which overestimate the volatility if the mean return is not zero.

$$volatility_{Garman-Klass} = \sigma_{GK}\sqrt{\frac{F}{N}}\sqrt{\sum_{i=1}^{N}\frac{1}{2}(Ln(\frac{h_i}{l_i})^2-(2Ln(2)-1)(Ln(\frac{c_i}{o_i})^2} \quad \text{Equation 2.4.2.5}$$

The first measurement that does not need to assume average return to be zero is called Rogers-Satchell volatility (Rogers and Satchell, 1991). It uses open, close, high and low prices. However, it still does not solve the problem of overnight jumps.

$$volatility_{Rogers-Satchell} = \sigma_{RS}\sqrt{\frac{F}{N}}\sqrt{\sum_{i=1}^{N} Ln\left(\frac{h_i}{c_i}\right)Ln(\frac{h_i}{o_i}) + Ln\left(\frac{l_i}{c_i}\right)Ln(\frac{l_i}{o_i})}$$

Equation 2.4.2.6

However, all these three measurements assume continuous trading while most of the actual trading is in discrete time period. Compare to close-to-close method; these estimators have significant gains in efficiency. Also, these three methods require seven times less observation than in close-to-close estimator in order to get the same statistical precision.

Yang-Zhang (OHLC)

Yang-Zhang (2000) modified Garman-Klass model by taking into account the changes from closing price at time t-1 to opening price at time t. This modified method solves the overnight jump problem, but it does not handle the drift assumption (zero mean return).

$$volatility_{GKYZ} = \sigma_{GKYZ} = \sqrt{\frac{F}{N}}\sqrt{\sum_{i=1}^{N}(Ln\left(\frac{o_i}{c_{i-1}}\right))^2 + \frac{1}{2}(Ln\left(\frac{h_i}{l_i}\right))^2 - (2Ln(2)-1)(Ln\left(\frac{c_i}{o_i}\right))^2}$$

Equation 2.4.2.7

In 2000, Yang-Zhang developed the most powerful volatility measurement which solves both overnight jump and drift problem. It combined Garman-Klass measurement with Rogers-Satchell measurement and modified by including overnight volatility and open to close volatility. This method assumes continuous trading at all time, which will also underestimate the volatility slightly. The estimator is given as below:

$$volatility_{Yang-Zhang} = \sigma_{YZ}$$
$$= \sqrt{F}\sqrt{\sigma_{overnight\ volatility}{}^2 + k\sigma_{open\ to\ close\ volatility}{}^2 + (1-k)\sigma_{RS}{}^2}$$ Equation 2.4.2.8

$$k = \frac{0.34}{1.34 + \frac{N+1}{N-1}}$$

$$\sigma_{overnight\ volatility}{}^2 = \frac{1}{N-1}\sum_{i=1}^{N}[Ln\left(\frac{o_i}{c_{i-1}}\right) - \overline{Ln(\frac{o_\iota}{c_{\iota-1}})}]^2$$

$$\sigma_{open\ to\ close\ volatility}{}^2 = \frac{1}{N-1}\sum_{i=1}^{N}[Ln\left(\frac{c_i}{o_i}\right) - \overline{Ln(\frac{c_\iota}{o_\iota})}]^2$$

When estimating the model, the square of the historical yang-zhang volatility estimator will be employed, denoted as the following:

$$\sigma^2_{yang-zhang}$$
$$= \{\sqrt{F}\sqrt{\sigma_{overnight\ volatility}{}^2 + k\sigma_{open\ to\ close\ volatility}{}^2 + (1-k)\sigma_{RS}{}^2}\}^2$$ Equation 2.4.2.9

2.4.3. ARCH and GARCH

Let R_t be price return of assets, an ARCH(q) process could be defined as the following:

$$y_t = \mu + \varepsilon_t$$
$$\{\varepsilon_t|\phi_t\}\sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = w + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2$$ Equation 2.4.3.1

where μ is the mean of series y_t, error term ε_t is a series of return residuals, ϕ_t represents the past information set, ε_t^2 is also known as ARCH term. The ARCH model allowed data to decide the optimal weights to use in forecasting the variance conditional on past information rather than fixing the number of most recent observations which assumes the variance of return is equally weighted for that fixed period, i.e. rolling standard deviation. Hence, ARCH provides reasonable forecasting.

Based on ARCH model, another model provides better ability in forecasting variance. GARCH(p,q) model added p-lag GARCH terms into the variance equation of ARCH(q) model which is expressed as the following:

$$y_t = \mu + \varepsilon_t$$
$$\{\varepsilon_t | \phi_t\} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

Equation 2.4.3.2

Similar to rolling standard deviation technique, GARCH model also uses weighted average of past variance but with declining weight that never dies away. Therefore, the new information weights more than old information which could be used to deal with clustering volatility effectively.

There exist a wide range of GARCH types models including EGARCH, GARCH-M, TGARCH which are the most popular used types of GARCH models. Nelson's univariate Exponential generalized autoregressive heteroskedastic model, EGARCH(p,q), could be defined by the following equation:

$$\ln(\sigma_t^2) = w + \sum_{k=1}^{q} \alpha_k g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \ln(\sigma_{t-k}^2)$$

Equation 2.4.3.3

Where w is the constant term, $Z_t = {}^{\varepsilon_t}/_{\sigma_t}$ represents the standardized residual, $g(Z_{t-k}) = \emptyset Z_{t-k} + \varphi\big(|Z_{t-k}| + E(Z_{t-k})\big)$ is a function of both magnitude and the sign of Z_{t-k}, which could be measured by the coefficients $\emptyset$ and φ respectively. $|Z_{t-k}|$ represents the modulus of Z_{t-k}. $E(Z_{t-k})$ represents the expected value of Z_{t-k}. This model allows volatility to react asymmetrically to negative and positive news.

While time series structure is good at forecasting, it does not help in explaining causes of volatility. Therefore, it might be helpful to directly include exogenous variables into the GARCH model which is called GARCH-M model. GARCH-M has the same structure as GARCH model except that there also exist heteroskedastic term in the mean equation of GARCH model. It is shown as follow:

$$y_t = \mu + \lambda\sigma_t + \varepsilon_t$$
$$\{\varepsilon_t|\phi_t\} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

Equation 2.4.3.4

2.4.4. Range-based GARCH

Molnar (2012) proposed a range GARCH(1,1) model that modifies the GARCH(1,1) model by replacing the ARCH term with a historical range-based volatility estimator, which is defined as the following:

$$y_t = \mu + \varepsilon_t$$
$$\{\varepsilon_t|\phi_t\} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \sigma_{yz,t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

Equation 2.4.4.1

Where $\sigma_{yz,t-i}^2$ represents the yang-zhang volatility estimator.

In addition, this chapter considers the yang-zhang volatility estimator as an exogenous variable in the conventional EGARCH and EGARCH-M models and propose the range EGARCH model which considers open, high, low and close prices. An EGARCH(1,1) with one lag of yang-zhang volatility estimator is defined as the following:

$$y_t = \mu + \varepsilon_t$$
$$\{\varepsilon_t|\phi_t\} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 + \gamma\sigma_{yz,t-1}^2$$

Equation 2.4.4.2

Where γ is a parameter of the yang-zhang volatility estimator, $\sigma^2_{yz,t-1}$.

2.4.5. Arbitrage opportunity

The linear regression is employed to examine the arbitrage opportunity across the exchange market by looking at the correlation between two returns, shown as the following:

$$R_{i,t} = \omega + \delta_j R_{j,t} + \varepsilon_t$$ *Equation 2.4.5.1*

Where ω is the constant term, and δ_j is a coefficient of variable $R_{j,t}$. Both $R_{i,t}$ and $R_{j,t}$ represent the Bitcoin return for exchange market i and j respectively, with i=1 being fixed, and j=2,3,4 and 5. $\varepsilon_t \sim N(0, \sigma_t^2)$. The number 1,2,3,4 and 5 indicate five different exchange markets. The null hypothesis is set as the following to examine the arbitrage opportunity:

$$H_0: \omega = 0 \ \& \ \delta_j = 1$$

If the above null hypothesis is rejected, then there is lack of evidence suggesting the Bitcoin returns are different between two exchange markets. Hence, there is evidence suggesting the existence of arbitrage opportunity between two exchange markets. Notice that, no arbitrage costs is assumed.

2.5. Data

2.5.1. Basic description

Daily data on Bitcoin prices were collected from five US dollar-based exchange markets on dc-charts.com/bitcoin. These five exchange markets are Bitstamp, Bitfinex, Okcoin, CEX.IO and HitBTC. The Bitcoin prices are measured in four ways including intraday-high and intraday-low prices as well as the open and close prices. There are 999 observations for each price series which are range between 17/01/2015 and 11/10/2017. Two different approaches are employed in this chapter in order to answer the research questions. The first approach examines the price movement of the Bitcoin price via investigating the predictability of Bitcoin return. The Bitcoin prices are collected from Bistamp exchange market between 17/10/2015 and 11/10/2017. The second approach examines whether there exists arbitrage opportunity across the exchange markets. Therefore, all data from the exchange markets are used for this approach.

Note that the price series data were missing for all five exchange market on the 19th of April 2015. Therefore, the data is filled by the average of the prices on 18/04/2015 and 20/04/2015. The open and close price are collected at 00:00 and 23:45. Unlike traditional financial market such as stock market which opens in the morning and closes in the afternoon. The Bitcoin exchange markets operate 24 hours a day and 7 days a week. These exchange markets are US dollars based which attract more US investors than the rest of the world. The fact that it is operating globally makes it reasonable to assume that even at midnight, there will be plenty of trading taking place in these exchange markets. Malkiel (1992) defines an efficient capital market fully and correctly reflects all the related information in determining the asset prices. Therefore, if the Bitcoin market is efficient, then all four measures of prices should correctly reflect the Bitcoin price at the moment of trading. The intra-day high and low prices are considered because they might provide more information about the Bitcoin price movement.

Diagram 1 (2, 3, 4) shows the Bitcoin open (high, low, close) prices for Bitfinex, Bitstamp, CEX.IO, HitBTC and OkCoin exchange markets denoted as bitfo, bitso, cexo, hito, Okco where the last letter "o" indicate the "open" prices. Diagrams 2, 3 and 4 use the letter "h", "l" and "c" at the end of each notation to represent the "high", "low" and "close" prices. For example, "bitfh" represents the intra-day high price for Bitfinex exchange. These graphs show different exchange markets have different Bitcoin price movement. All exchange markets show Bitcoin price rises dramatically since the beginning of 2017. However, HitBTC exchange market is the only one that recovers quickly after the big drop in September of 2017 where the China government ban all cryptocurrency platforms. The HitBTC creates the new high record for the Bitcoin price immediately after the drop. The rest of the four exchange markets tend to have reacted slower to the big drop.

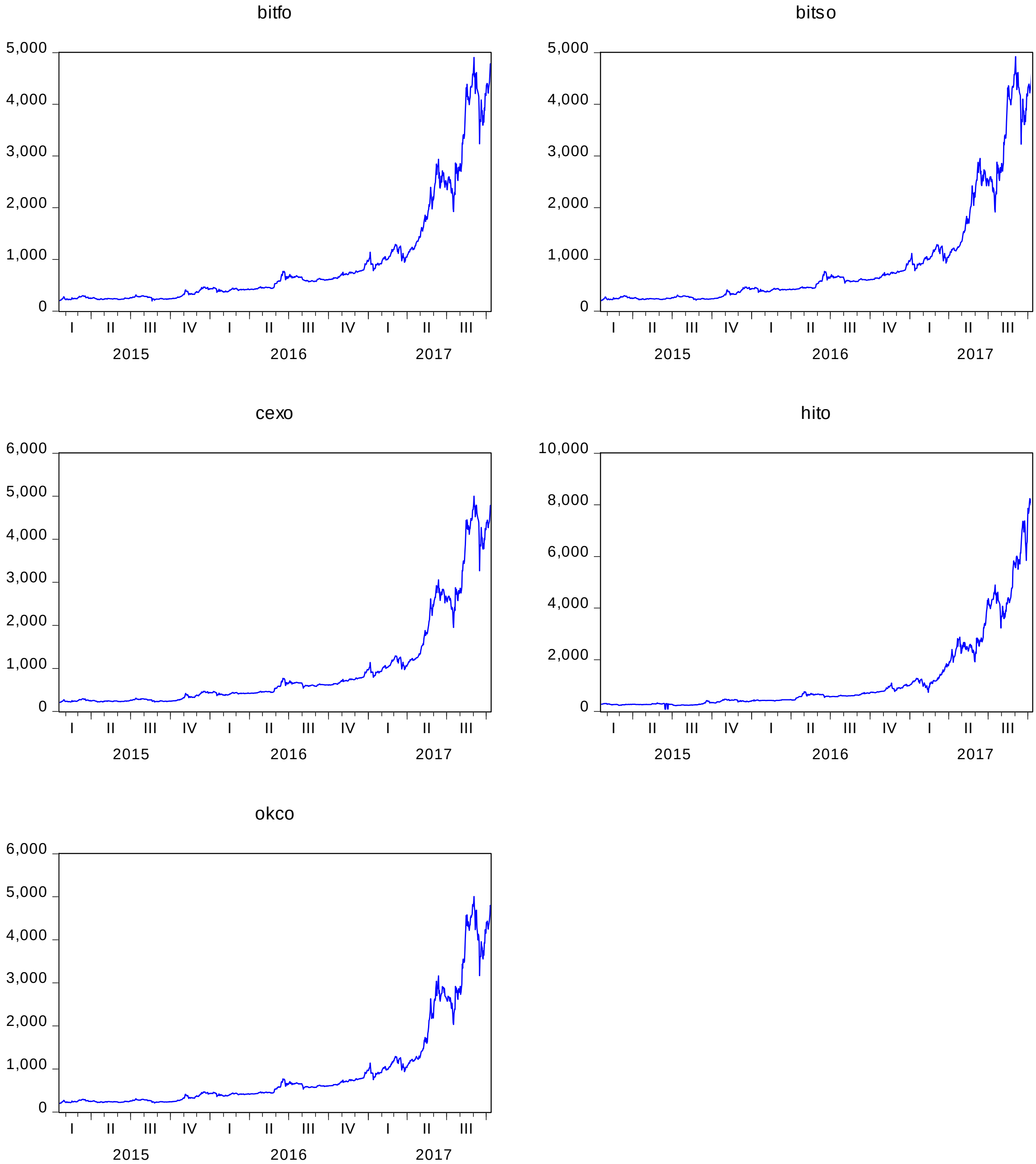


Diagram 1: Bitcoin open price for Bitfinex, Bitstamp, CEX.IO, HitBTC and OkCoin exchange markets. The open prices for these five Bitcoin exchange markets are similar to each other by looking at the graphs. Notice that the maximum open price for HitBTC exchange market has gone up to 8000 usd at the end of the sample periods. This could be due to lack of liquidity for HitBTC exchange market.

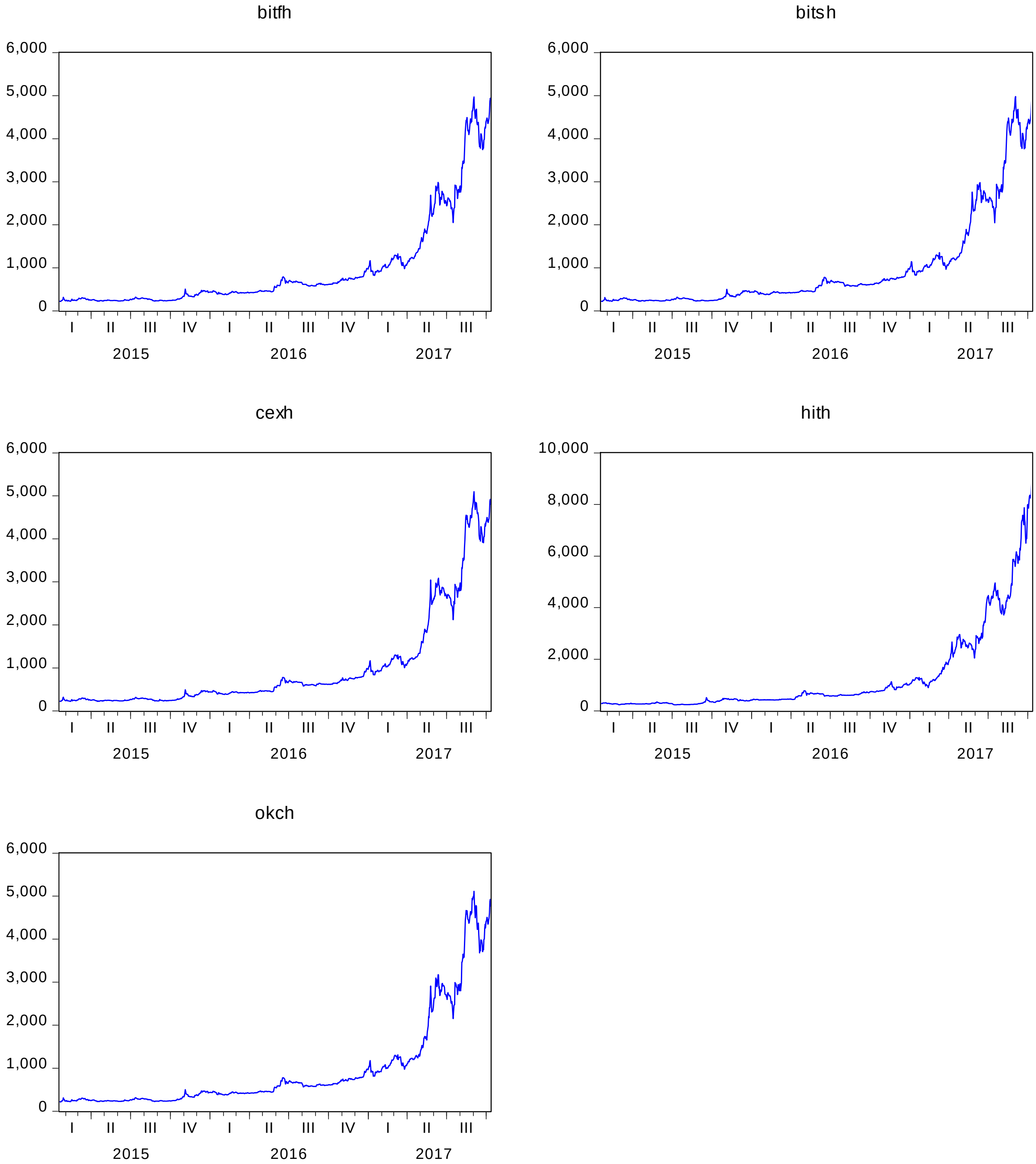


Diagram 2: Bitcoin intra-day high price for Bitfinex, Bitstamp, CEX.IO, HitBTC and OkCoin exchange markets. The Bitcoin price is behaving differently for HitBTC exchange market, especially at the end of the sample period.

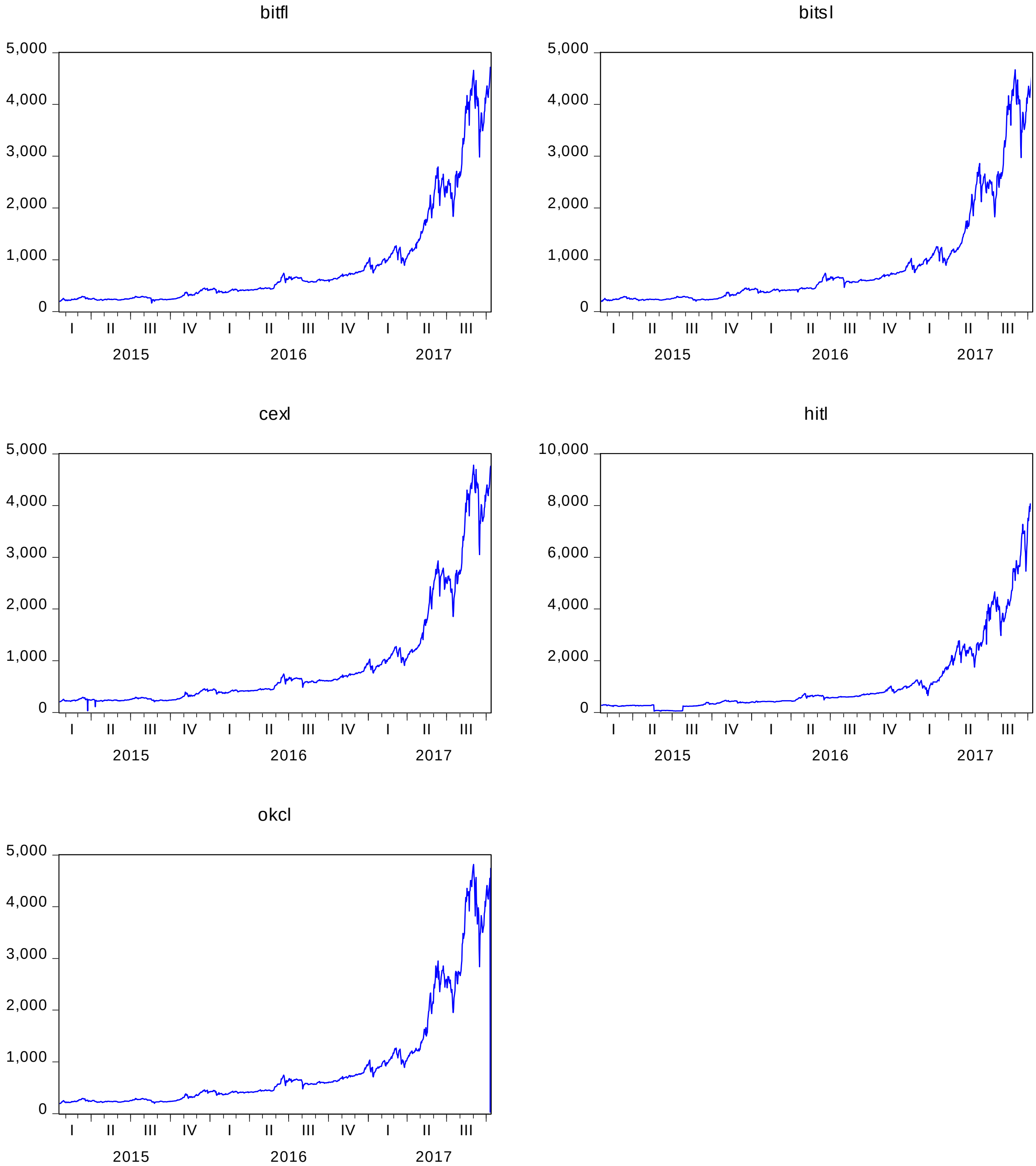


Diagram 3: Bitcoin intra-day low price for Bitfinex, Bitstamp, CEX.IO, HitBTC and OkCoin exchange markets. The Bitcoin low price plots are more volatility than open and close prices. Especially when the Bitcoin market is at turmoil at the end of sample period.

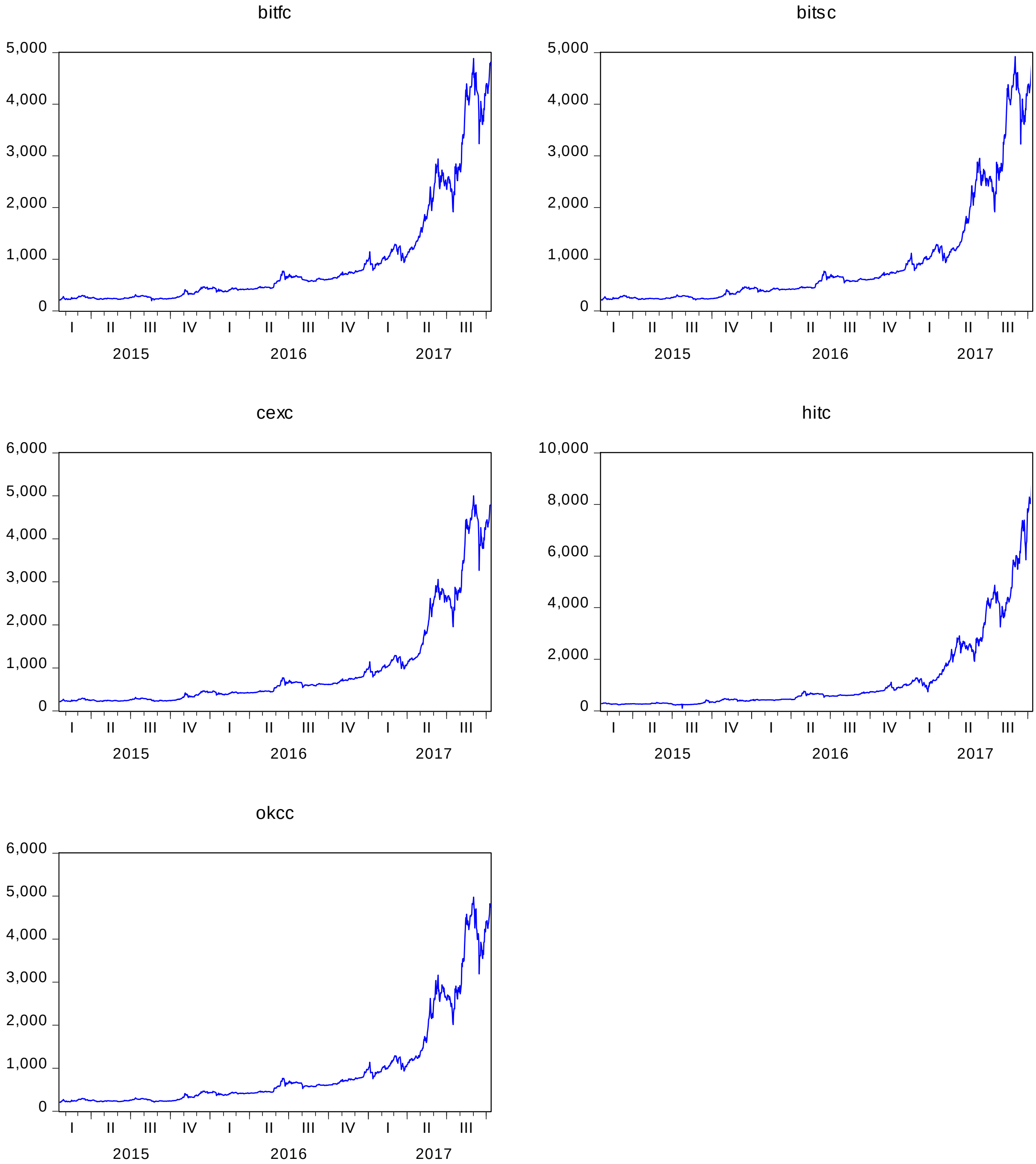


Diagram 4: Bitcoin close price for Bitfinex, Bitstamp, CEX.IO, HitBTC and OkCoin exchange markets. Similar to the open price of Bitcoin, the close price for Bitcoin at HitBTC exchange market varies a lots. It seems that bitcoin closing price at HitBTC exchange market recovers sooner than other exchange markets.

Diagram 5 shows the price difference of Bitfinex exchange market against other four exchange markets. For illustration purpose, only the close prices for each exchange market are used in this diagram. Bitfinex is chosen as a reference exchange market because it has the largest trading volume among five exchange markets. But this does not mean that other exchange markets are less important. As the diagram 5 shows, the price difference before the year of 2017 is relatively small. Although there is some significant difference in the June of 2016 when comparing to Bitstamp, CEXio and OKcoin exchange markets. In the May of 2016, the average of Bitcoin price across exchange markets are around 500 US dollar, but the price difference can reach to nearly 80 US dollars difference which is around 15% of differences. Between 01/01/2017 and the end of the sample period, the median and maximum price for Bitcoin is 2012.70 and 4886.60 US dollars for the Bitfinex exchange market. Therefore, at the end of the sample period, the 4000 US dollars difference between Bitfinex and HitBTC is enormous. Overall, it fluctuates around price difference of zero US dollar for these three exchange markets. It is interesting that the price difference between Bitfinex and HitBTC exchange markets has a cycle pattern even before the year of 2017. The price difference graph between these two exchange markets shows Bitfinex has larger Bitcoin trading price when the curve is slowing moving upward where the price difference is positive value. The price difference starts to decrease and drops below the zero mean indicating the Bitcoin trading price at HitBTC exchange is greater than Bitfinex. Such pattern becomes more obvious after 2016. At the beginning of 2017, the Bitcoin price at Bitfinex is greater than Bitstamp, CEXio and OkCoin but becomes smaller in the second quarter of 2017. The price difference between Bitfinex and HitBTC shows three clear cycle pattern in 2017 where the cycle becomes more obvious when reaching the end of the sample period. Such a cycle pattern could also be found between Bitfinex and OkCoin exchange markets. However, the cycle is moving upward instead of moving downward indicating the price difference becomes smaller. In summary, these four plots in diagram 5 indicate the existence of arbitrage opportunity across exchange markets.

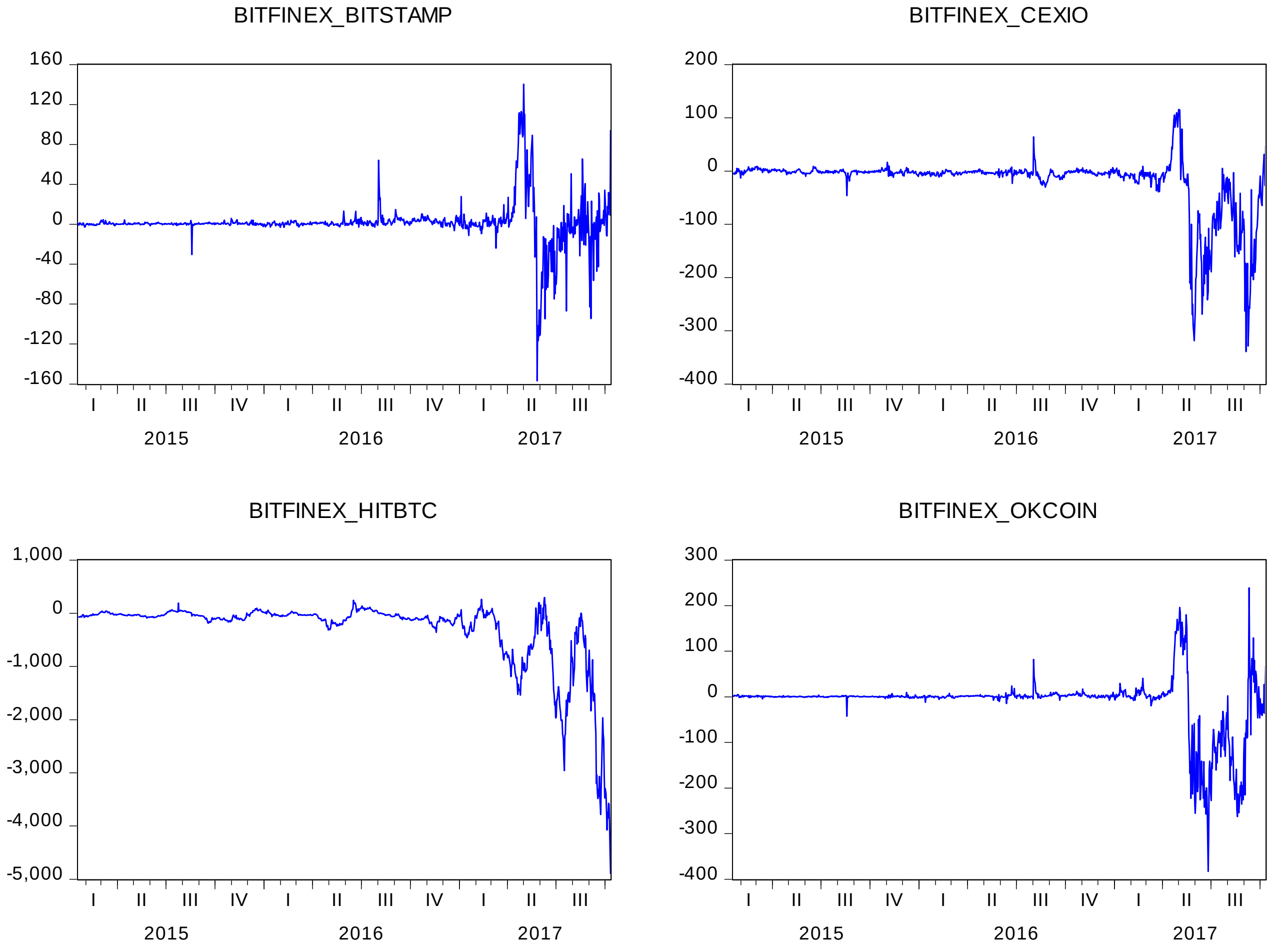


Diagram 5: Price difference across exchange markets using close price.

Table 1 below shows the descriptive statistics across five exchange markets. The median values are the similar. The HitBTC has the largest Bitcoin price range where the minimum price is 96 US dollars, and the maximum price is 9727 US dollars. The minimum and maximum values for the HitBTC exchange market is half of the minimum values for the other exchange markets, and the maximum value is twice as large as the other four exchange markets. It is also the most volatile exchange market with standard deviation value of 1632. All of them have positive skewness and large kurtosis suggesting the distribution is skewed to the right with heavy tails. In addition, the Jarque-Bera test rejects the null hypothesis of normal distribution.

	BITFC	BITSC	CEXC	HITC	OKCC
Mean	940.5194	939.1159	959.5446	1248.507	951.3721
Median	531.0000	527.6400	536.1243	594.7600	532.0100
Maximum	4886.600	4921.700	4999.990	9727.720	4977.000
Minimum	194.5238	199.6900	207.0333	96.31000	197.7900
Std. Dev.	1060.821	1062.876	1097.303	1632.987	1091.410
Skewness	2.094138	2.093785	2.086573	2.411422	2.091333
Kurtosis	6.562804	6.533197	6.465777	8.702519	6.474218
Jarque-Bera	1258.541	1249.550	1224.888	2321.782	1230.638
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	939578.8	938176.8	958585.0	1247259.	950420.7
Sum Sq. Dev.	1.12E+09	1.13E+09	1.20E+09	2.66E+09	1.19E+09

Table 1: Descriptive statistics of the close price across five Bitcoin exchange markets including Bitfinex, Bitstamp, CEX, HitBTC and OkCoin. The details are covered in the above paragraph.

2.5.2. Unit root test

The augmented dickey fuller unit root test[2] is employed to examine the stationarity of the Bitcoin price series. Results indicate all Bitcoin price including open, high, low and close price series have unit root since the p-values of the unit root test is greater than 0.1 which cannot reject the null hypothesis of existence of unit root. The log return of these series will be calculated using the following formula:

$$R_t = \log(\frac{P_t}{P_{t-1}})$$

Equation 2.5.2.1

Where R_t and P_t represent the log return and the price of Bitcoin at time t. In the following, a new set of notation is given to the log returns of Bitcoin. First, I number the exchange markets Bitfinex, Bitstamp, CEX.IO, HitBTC and OkCoin into 1, 2, 3, 4, and 5. The letter “o”, “h”, “l” and “c” at the end of each notation represent the “open”, “high”, “low” and “close” prices. Therefore, $RO_{1,t}$, $RO_{2,t}$, $Ro_{3,t}$, $RO_{4,t}$ and $RO_{5,t}$ represent the log return of Bitcoin calculated by open price for exchange market Bitfinex, Bitstamp, CEX.IO, HitBTC and OkCoin respectively.

[2] Other options of unit root tests include Phillps-Perron test, KPSS test, Zivot-Andrews test and so on.

2.5.3. Price differences among exchanges

Diagram 6 shows the log return for Bitcoin calculated by using close prices. The unit root test results indicate these series are stationary. The Bitcoin return is significantly larger in mid of 2015 for OkCoin exchange market, RC5, indicating the price difference between two consecutive periods is large, which also suggest a potential of arbitrage opportunity. However, such a large difference between two consecutive periods is not common even for the same exchange market. For instance, RH5 in diagram 6 shows the Bitcoin return calculated using high price which has similar characteristics to the other returns. Although editing the close price data for OkCoin could get rid of the anomaly data but this will also biased to market efficiency hypothesis. Therefore, raw data is used in this case. Moreover, it is clear to observe each return series exhibits heteroscedasticity property since there exist volatility clustering in these plots. Therefore, autoregressive conditional heteroskedasticity (ARCH) is suitable to use.

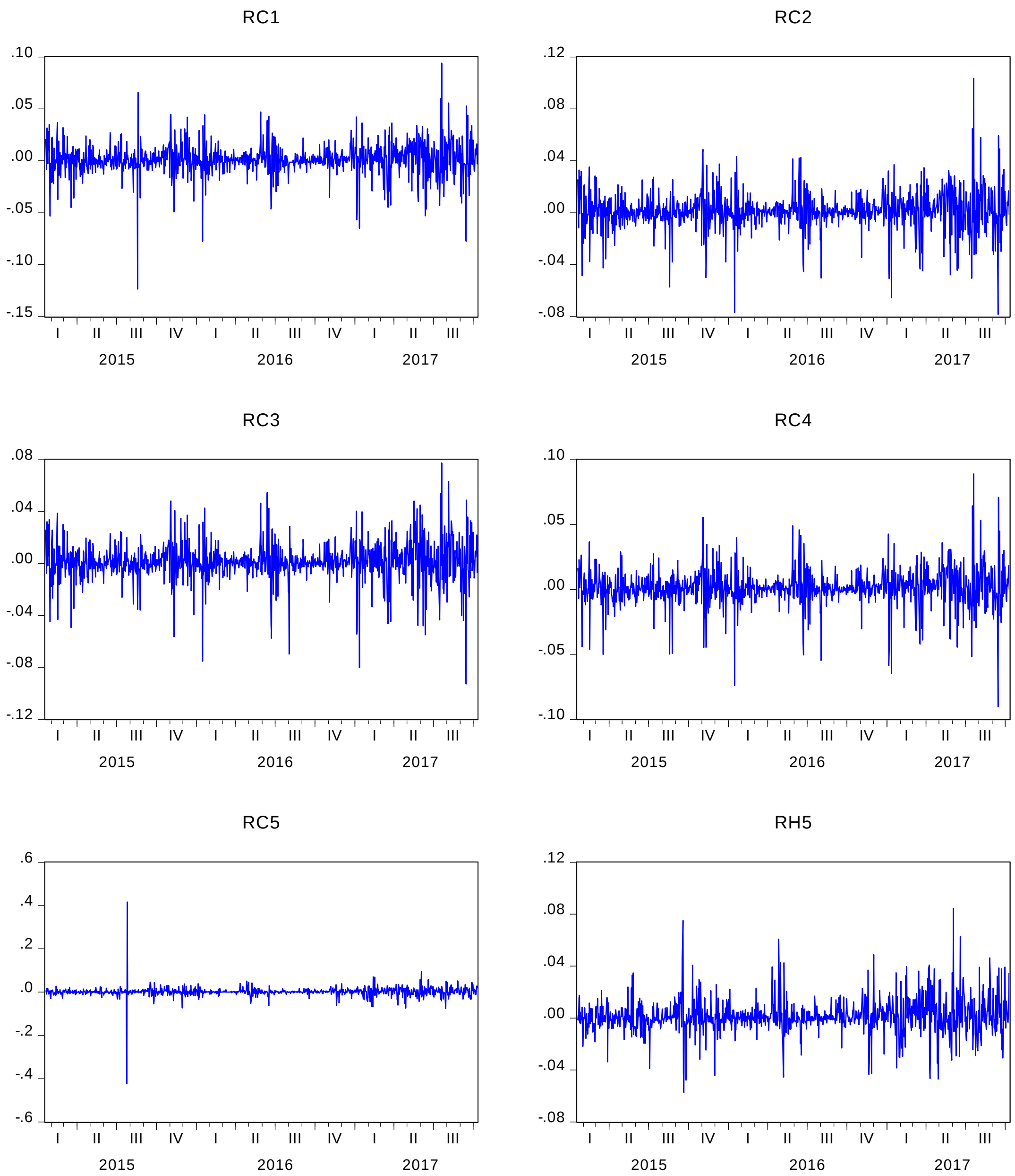


Diagram 6: Log return of Bitcoin price

In addition to the above data, the Litecoin prices are also collected from the Bitfinex exchange market in order to investigate the predictability of Bitcoin return via examining granger causality effect from Litecoin market to Bitcoin market. Litecoin is chosen to be for comparison because Litecoin shares some similar properties as Bitcoin such as decentralization and they are the first to introduce SHA256 and Scrypt cryptographic hashing functions. The focus of this chapter is to examine whether Bitcoin market is efficient. Therefore, the details of Litecoin including its features and technology will not be discussed until the next chapter. In the following chapter, the dynamic relationship between Bitcoin and Litecoin will be discussed in details. Diagram 7 shows the log return of Litecoin calculated by open, high, low and close prices, which are denoted as lro, lrh, lrl and lrc. The “l” in the front represents “Litecoin". The plots indicate volatility clustering, which is more obvious in the year of 2017 where the Litecoin price becomes more volatile. It is interesting to note that asymmetric effect of the volatility which indicates an exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model might be appropriate to use.

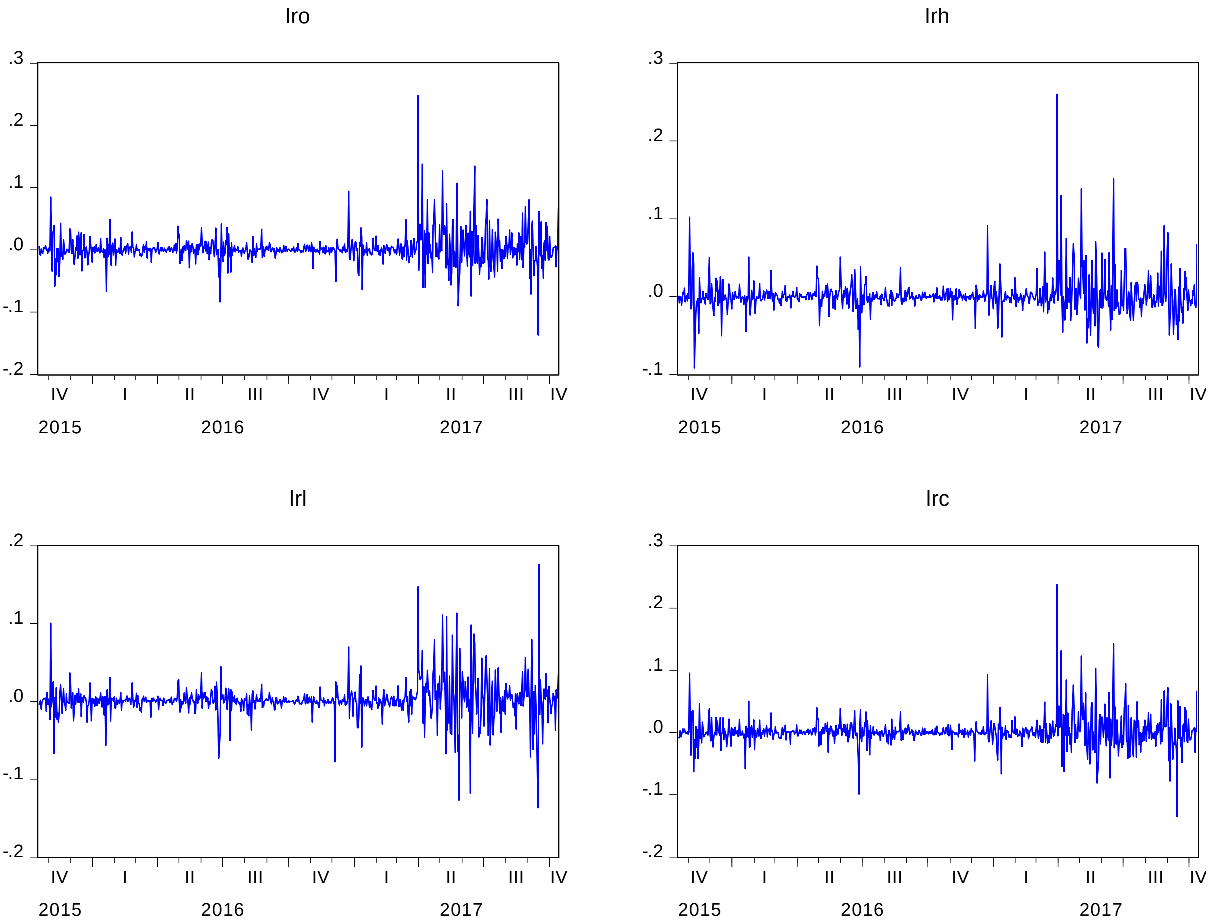


Diagram 7: Log return of Litecoin calculated using open, high, low and close prices.

2.5.4. Historical volatility estimator

As mentioned above, one of the contributions in this study is to consider the extreme data in analysing the volatility of Bitcoin. Diagram 8 shows the Bitcoin historical volatility estimator, denoted as "vol5", which is calculated using the Yang-Zhang volatility estimator approach using 5-days-rolling-window. The ADF unit root test result indicates vol5 series is stationary at 5% level.

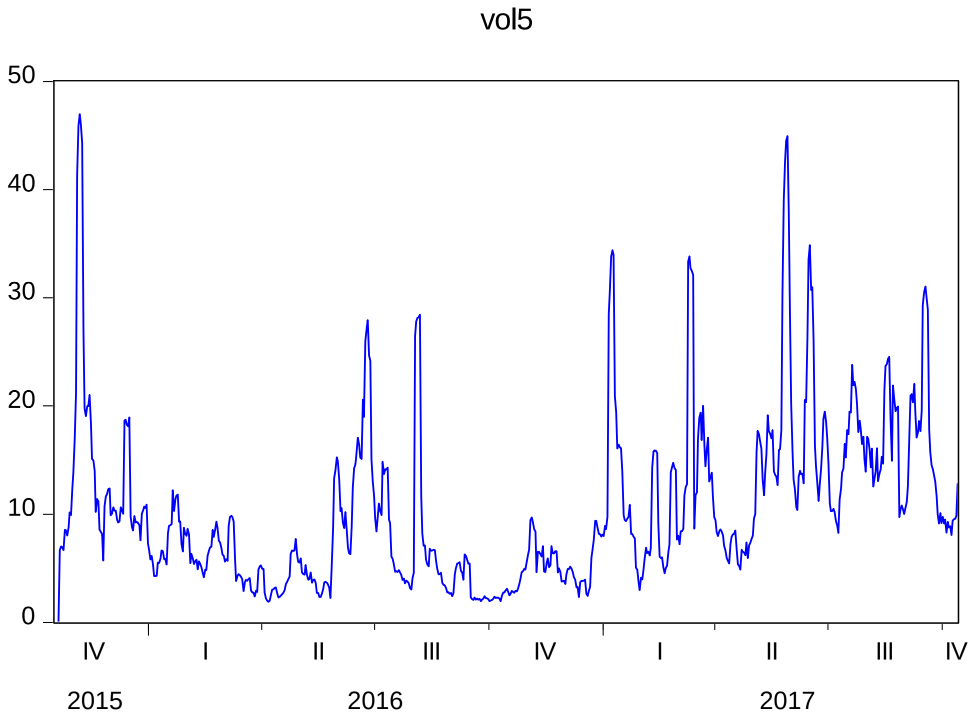


Diagram 8: The Yang-Zhang volatility estimator for Bitcoin using 5-days-rolling-window.

2.6. Results and discussion

This section discusses the results on the Bitcoin price return predictability on the Bitstamp exchange market and the results on the arbitrage opportunities across five US dollar-based Bitcoin exchange markets. This chapter only examines the return predictability and arbitrage opportunity in the short run rather than long run. The next chapter will try to investigate the dynamic relationship between Bitcoin and Litecoin returns in both short and long run.

For the return predictability part, autoregressive model (AR model) has been employed for the conditional mean equations along with different types of GARCH models for conditional variance equations. In order to examine whether historical range data based volatility estimator (yang-zhang volatility estimator) is useful in predicting the future conditional variance, GARCH with exogenous variable (GARCH-X) will be employed for the conditional variance equations. Both conventional GARCH type models and range-based GARCH type models will be estimated for comparison purposes. In addition, autoregressive model along with some exogenous variables are used to examine whether the lag of the returns that are calculated using intra-day data open, high, low and close prices are useful in predicting the current returns. Moreover, the autoregressive model with yang-zhang volatility estimator included in the conditional mean equation will examine whether historical range data based volatility estimator is helpful in predicting the Bitcoin return. In the end, the lag of the price return of Litecoin will be used to examine whether Litecoin return granger causes the Bitcoin return. For the arbitrage opportunity part, the relationships among the Bitcoin returns across exchange markets are examined using ordinary least square regression along with GARCH model for the conditional variance equation.

2.6.1. Return predictability in Bitstamp

2.6.1.1. AR(1)-GARCH and AR(1)-Range-GARCH models

The open, high, low and close Bitcoin prices are used to calculate Bitcoin returns denoted as $ro_{2,t}$, $rh_{2,t}$, $rl_{2,t}$, $rc_{2,t}$, where "2" indicates the "Bitstamp" exchange market as mentioned in the data section. Each of the $ro_{2,t}$, $rh_{2,t}$, $rl_{2,t}$ and $rc_{2,t}$ return series is used as a dependent variable in the AR model with the lags of their own returns. The optimal lag length is chosen to be 1 according to Bayesian information criterion. Before including the GARCH models, each of the AR(1) model is estimated. Results suggest only the lag of $rh_{2,t}$ is significant in predicting the $rh_{2,t}$. The residual diagnostic test results suggest the existence of ARCH effect. Therefore, different types of GARCH models will be considered in order to remove the heteroscedasticity characteristics. Table 2, 3 and 4 show the results of AR(1) model with different conditional variance models including GARCH(1,1), GARCH(1,1)-M, EGARCH(1,1) and EGARCH(1,1)-M models. Also the results of AR(1) models with conditional variance model that considers range-data. Note that the RGARCH(1,1) model has been employed by Molnar (2012) to examine the stock return volatility. In addition, the Range-EGARCH(1,1) model is employed, where the yang-zhang volatility estimator is used as an exogenous variable in the conditional variance equations. Note that Molnar (2012) uses Parkinson volatility estimator (1980) instead of Yang-zhang volatility estimator for the Range-GARCH model. The reason to include the yang-zhang volatility estimator in the conditional variance equation is to examine the predictability of the historical range data based volatility estimator on the volatility, and it does not underestimate the volatility estimator like Parkinson volatility estimator. Moreover, the related conditional variance will be included in the conditional mean equation in order to examine the predictability of the Bitcoin return.

For the conditional mean equations, results indicate only the $rh_{2,t-1}$ is significant in predicting its own current return for the conventional AR(1)-GARCH model. When Range-GARCH model is employed, $rl_{2,t-1}$ becomes significant in predicting its own current return at 10% significant level while $ro_{2,t-1}$ and $rc_{2,t-1}$ stay insignificant in predicting their own current returns for all the AR(1)-Range-GARCH models. Results indicate the coefficients on explanatory variables in the conditional variance equations for all the conventional GARCH models are highly significant. But for the Range-GARCH models, results indicate only Range-EGARCH and Range-EGARCH-M are suitable for estimation. Therefore, yang-zhang volatility estimator is only significant when exponential GARCH model is considered. It does not provide any information in predicting the conditional volatility for RGARCH model which is introduced by Molnar (2012) because Molnar suggests that ARCH term could be replaced by the historical volatility estimator. Note that when ARCH terms are kept in the conditional variance equations and include yang-zhang volatility estimator as an exogenous variable, then the coefficients on the ARCH term, GARCH term and yang-zhang volatility estimator become highly significant. Such results imply lots of information is hidden in the residuals and yang-zhang historical volatility estimator does provide more information in predicting the current volatility.

In the following, only the models with returns calculated using intra-day high price will be discussed because most of the $ro_{2,t-1}$, $rl_{2,t-1}$ and $rc_{2,t-1}$ variables are not significant in predicting their own current returns. As Table 3 shows all constant terms and $rh_{2,t-1}$ variable is highly significant in the conditional mean equations. However, results suggest conditional volatility is not useful in predicting the current return. For the conventional AR(1)-GARCH models (GARCH(1,1), GARCH(1,1)-M, EGARCH(1,1), EGARCH(1,1)-M), results indicate an increase in the lags of the returns by 1% will lead to an increase of current return by around 0.13%. For the AR(1)-Range-GARCH models, such influence is increased when EGARCH is considered, where an increase of 1% in the lags of returns will lead to an increase of 0.22% increase in current returns. Based on Akaike information criteria, EGARCH and Range-EGARCH model are preferable than GARCH and RGARCH models. Moreover, the Range-EGARCH model is preferable than EGARCH model. The following shows the estimated conditional variance model using Range-EGARCH model.

$$\ln(\sigma_t^2) = w + \alpha \ln(\sigma_{t-1}^2) + \emptyset Z_{t-1} + \varphi\big(|Z_{t-1}| + E(Z_{t-1})\big) + \beta \sigma_{yz,t-1}^2 \qquad \text{Equation 2.6.1.1.1}$$

Where $Z_{t-1} = {}^{\varepsilon_{t-1}}/_{\sigma_{t-1}}$ represents the standardized innovation in period t-1 with ε_{t-1} being the innovation and σ_{t-1} being the volatility in period t-1. The coefficient w=-13.89*** represents the constant term, $\alpha = -0.378^{***}$ measures the persistence which determines the influence of the past conditional volatility on the current conditional volatility. Similarly, $\beta = 0.154^{***}$ measures the influence of the past historical yang-zhang volatility on the current conditional volatility. Both $\emptyset$ and φ measure the asymmetric effect, whereas $\emptyset = 0.0934^{***}$ measures sign effect and $\varphi = 0.07708^{***}$ measures the size effect. Note that *** indicates the corresponding coefficients are significant at 1% level. Since the magnitudes of both α and β are less than 1, the conditional volatility process is stationary. The positive coefficient of $\emptyset$ indicates that there does not exist leverage effect which suggests a positive and negative innovation in the previous period will lead to the same effect to the conditional volatility in the current period. Alternatively, the asymmetric effect of the standardized innovations on the volatility could be measured by the derivatives from the following:

$$\frac{d(\emptyset Z_t + \varphi(|Z_t| + E(Z_t)))}{d(Z_t)} = \begin{cases} 1 + \emptyset & for\ Z_t > 0 \\ -1 + \emptyset & for\ Z_t < 0 \end{cases}$$ *Equation 2.6.1.1.2*

The relative asymmetry could be defined by $\frac{|-1+\emptyset|}{(1+\emptyset)} \approx 0.857 < 1$, which implies for positive asymmetry. Furthermore, note that the past conditional volatility has negative impact on the current conditional volatility while past yang-zhang volatility has positive impact on the current conditional volatility. A 1% (1 unit) increase in the past conditional volatility (yang-zhang volatility) will lead to decrease (increase) of the current conditional volatility by 0.38% and 0.15%. The persistence of the volatilities could be examined by the half-life which is the time taken for half of the influence to disappear:

$$Half\ life = \frac{\ln(0.5)}{\ln(\gamma)}$$ *Equation 2.6.1.1.3*

Where $\gamma = \alpha$, β. Results indicate it requires 0.71 (0.37) day for the shock from the past conditional volatility (yang-zhang volatility) to reduce to one-half of their original size which implies a very short persistence in both shocks.

The residual diagnostic test results for all estimated model using $rh_{2,t}$ as the dependent variable suggest there is no serial autocorrelation and heteroscedasticity in the residuals. However, the Jaqure-Bera test results suggest the residuals are not normally distributed. The adjusted residual sum of squares suggests only 0.04% of the dependent variables is explained. Therefore, in the following section, more explanatory variables will be considered and examine whether they could improve the return predictability.

2.6.1.2. AR model with exogenous variables

This section considers the AR(1) conditional mean model with $rh_{2,t}$ being the dependent variable and its own lag, $rh_{2,t-1}$, along with $ro_{2,t-1}$, $rl_{2,t-1}$ and $rc_{2,t-1}$ being the explanatory variables. The same types of GARCH models from the above section are used to estimate the conditional variance equations. Contradict to the last section, the $rh_{2,t-1}$ variable has negative impact on its current return, and the influence is greater. An increase of 1% in, $rh_{2,t-1}$ will lead to decrease of current return by roughly 0.4% (0.34%) if conventional GARCH models (Range-EGARCH models) are used. Another two variables, $ro_{2,t-1}$ and $rc_{2,t-1}$ are positively correlated with the current return. If the conventional GARCH models are employed, an increase of 1% in $ro_{2,t-1}$ and $rc_{2,t-1}$ will lead to increase of roughly 0.20% and 0.70% in current return respectively. Results are similar if Range-GARCH models are employed instead. As shown in the last section, none of the conditional variances is significant in predicting the current return. Agrees with the previous results, leverage effect does not exist. But the influence of the past volatility becomes larger while the yang-zhang volatility becomes less influence on the current conditional volatility. The residual diagnostic tests suggest no serial correlation, the ARCH effect exist in the residuals. However, the p-value rejects the null hypothesis of normally distributed for the Jaqure-Bera test. The adjusted residual sum of squares increases to 0.30, which implies 30% of the dependent variable could be explained by the explanatory variables.

Furthermore, the AR(1) conditional mean model with $rh_{2,t}$ being the dependent variable is regressed on different yang-zhang historical volatility estimators each with a different number of rolling windows which are chosen to be 2, 3, 4, 5, 6 and 7. Each of these six estimators will be tested for the return predictability. The following results suggest only the yang-zhang volatility estimators with rolling window 2, 3 and 4 are significant in predicting the return. The following show the AR(1) with exogenous model with GARCH(1,1) is estimated as below:

$$rh_t = -0.0019 + 0.12 * rh_{t-1} - 0.00013 * \sigma^2_{yz4,t-1} + \varepsilon_t \qquad \text{Equation 2.6.1.2.1}$$
$$\sigma^2_t = 0.000004 + 0.17 * \varepsilon^2_{t-1} + 0.82 * \sigma^2_{t-1}$$

Where $\sigma^2_{yz4,t-1}$ represents the yang-zhang volatility estimator with rolling window of 4. Here only one estimated model is discussed because the coefficients have similar magnitude and they are all significant at 1% level. Results suggest an increase in historical volatility will reduce the current expected return. This is reasonable because the increase in volatility will reduce market performance which will lead to decrease in demand or increase in supply of Bitcoin.

2.6.1.3. Granger causality test

Dong et al., (2013) suggest a Granger causality test could be used to examine the efficient market hypothesis. In this section, another cryptocurrency, Litecoin, is used to examine whether the historical information of Litecoin return has predictability power in the current Bitcoin return. To construct the Granger causality test, the $rh_{2,t}$ is regressed on its own lag and a lag of Litecoin return that is calculated by high price, denoted as lrh_{t-1}. The following shows the conditional mean equation:

$$rh_t = c + \alpha_1 rh_{t-1} + \beta_1 lrh_{t-1} + \varepsilon_t \quad \text{Equation 2.6.1.3.1}$$

Where c represents the constant term, α_1 and β_1 are the parameters of variables rh_{t-1} and lrh_{t-1} respectively, ε_t is the residual at time t.

Agrees to the previous two section that, all conventional GARCH models are highly significant as well as the range-EGARCH model. All the conditional volatilities are stable given that the sum of the coefficients on the ARCH term and GARCH term is less than 1 and the coefficient on the ln(σ^2_{t-1}) is less than 1.

For the conditional mean equations, each of the estimated model suggests lrh_{t-1} is positively correlated with as rh_t. However, the influence of the Litecoin return in the previous period, lrh_{t-1} on the current Bitcoin return, rh_t, is less than the influence of the rh_{t-1}. An increase of Litecoin return by 1% will lead to increase of Bitcoin current return by roughly 6%, whereas the lag of Bitcoin return, rh_{t-1}, will lead to roughly of 12% increase in its current return. Residual diagnostic test results suggest there do not exist serial correlation and heteroscedasticity in the residuals dataset. However, the adjusted residual sum of square remains as low as 0.037%.

2.6.2. Arbitrage opportunities across exchanges

This section examines whether there exist differences in returns across exchange markets using linear regression. All open, high, low and close prices are used to calculate the corresponding Bitcoin returns, denoted as $ro_{i,t}$, $rh_{i,t}$, $rl_{i,t}$ and $rc_{i,t}$ where ro, rh, rl, rc represents returns calculated using open, high, low and close prices respectively, for i=1,2,3,4,5. The number 1,2,3,4 and 5 corresponds to Bitfinex, Bitstamp, CEX.IO, HitBTC and OkCoin exchange markets.

In this section, an exchange market, Bitfinex, is chosen to be the reference exchange market and run the following conditional mean equations for four types of returns:

$$ro_{1,t} = \omega_{o,j} + \delta_{o,j} ro_{j,t} + \varepsilon_{o,t}$$ *Equation 2.6.2.1*

$$rh_{1,t} = \omega_{h,j} + \delta_{h,j} rh_{j,t} + \varepsilon_{h,t}$$ *Equation 2.6.2.2*

$$rl_{1,t} = \omega_{l,j} + \delta_{l,j} rl_{j,t} + \varepsilon_{l,t}$$ *Equation 2.6.2.3*

$$rc_{1,t} = \omega_{c,j} + \delta_{c,j} rc_{j,t} + \varepsilon_{c,t}$$ *Equation 2.6.2.4*

Where j=2,3,4 and 5 with null hypotheses being the following:

$$H_0: \omega_{o,j} = 0 \ and \ \delta_{o,j} = 1$$
$$H_0: \omega_{h,j} = 0 \ and \ \delta_{h,j} = 1$$
$$H_0: \omega_{l,j} = 0 \ and \ \delta_{l,j} = 1$$
$$H_0: \omega_{c,j} = 0 \ and \ \delta_{c,j} = 1$$

Given that all examined series exhibit ARCH effect, the GARCH models are considered in order to remove the heteroscedasticity. In this section, only the conventional GARCH models will be considered. Therefore, no range data based volatility estimator will be used. The following corresponding conditional variance equations show the GARCH(1,1) models for each of the above conditional mean equations:

$$\sigma_{oj,t}^2 = \kappa_{o,j} + \eta_{o,j} \varepsilon_{oj,t-1}^2 + \zeta_{o,j} \sigma_{oj,t-1}^2$$ *Equation 2.6.2.5*

$$\sigma_{hj,t}^2 = \kappa_{h,j} + \eta_{h,j} \varepsilon_{hj,t-1}^2 + \zeta_{h,j} \sigma_{hj,t-1}^2$$ *Equation 2.6.2.6*

$$\sigma_{lj,t}^2 = \kappa_{l,j} + \eta_{l,j} \varepsilon_{lj,t-1}^2 + \zeta_{l,j} \sigma_{lj,t-1}^2$$ *Equation 2.6.2.7*

$$\sigma_{cj,t}^2 = \kappa_{c,j} + \eta_{c,j} \varepsilon_{cj,t-1}^2 + \zeta_{c,j} \sigma_{cj,t-1}^2$$ *Equation 2.6.2.8*

Where $\kappa_{n,j}$ represents the constant terms for n=o, h, l and c which corresponds to open price return, high price return, low price return and close price return. $\eta_{n,j}$ and $\zeta_{n,j}$ represents the coefficients on the ARCH terms and GARCH terms, for n=o, h, l, and c.
Moreover, the EGARCH(1,1) model is also employed for conditional variance equations in the following way:

$$\ln\left(\sigma_{oj,t}^2\right) = w_{o,j} + \alpha_{o,j}\ln\left(\sigma_{oj,t-1}^2\right) + \emptyset_{o,j} Z_{oj,t-1} + \varphi_{o,j}\left(\left|Z_{oj,t-1}\right| + E\left(Z_{oj,t-1}\right)\right) \quad \text{Equation 2.6.2.9}$$

$$\ln\left(\sigma_{hj,t}^2\right) = w_{h,j} + \alpha_{h,j}\ln\left(\sigma_{hj,t-1}^2\right) + \emptyset_{h,j} Z_{hj,t-1} + \varphi_{h,j}\left(\left|Z_{hj,t-1}\right| + E\left(Z_{hj,t-1}\right)\right) \quad \text{Equation 2.6.2.10}$$

$$\ln\left(\sigma_{lj,t}^2\right) = w_{l,j} + \alpha_{l,j}\ln\left(\sigma_{lj,t-1}^2\right) + \emptyset_{l,j} Z_{lj,t-1} + \varphi_{l,j}\left(\left|Z_{lj,t-1}\right| + E\left(Z_{lj,t-1}\right)\right) \quad \text{Equation 2.6.2.11}$$

$$\ln\left(\sigma_{cj,t}^2\right) = w_{c,j} + \alpha_{c,j}\ln\left(\sigma_{cj,t-1}^2\right) + \emptyset_{c,j} Z_{cj,t-1} + \varphi_{c,j}\left(\left|Z_{cj,t-1}\right| + E\left(Z_{cj,t-1}\right)\right) \quad \text{Equation 2.6.2.12}$$

Where j=2,3,4 and 5. $w_{n,j}$ represent the constant terms where n=o, h, l and c. The coefficients $\alpha_{n,j}$ measure the persistence of past conditional volatility, for n=o, h, l, and c. The coefficients $\emptyset_{o,j}$ and $\varphi_{o,j}$

The GARCH-M model has been employed for each regression, but results indicate most of the conditional variance is not significant in the conditional mean equations. Therefore, results are not shown here. The GARCH(1,1) models do not provide stable conditional variance for most of the estimated equations. EGARCH(1,1) provides stable and significant conditional variance equations. However, the focus of this section is to examine whether there exist differences of Bitcoin returns across exchanges. The main purposes of the GARCH(1,1) and EGARCH(1,1) models are removing the ARCH effect in the residual series. Therefore, as long as the conditional variance equations are stable and significant. Then the estimated results will be analysed. In the following, the models with GARCH(1,1) model as the conditional variance equations will be analysed first. Then the models with EGARCH(1,1) will be analysed.

2.6.2.1. Linear regression with GARCH(1,1)

As discussed earlier, the reason for employing GARCH model rather than ARCH model is that GARCH model allows for time varying volatility. When close prices are used to calculate the Bitcoin returns, none of the estimated models has stable conditional variance models when GARCH(1,1) is employed, except for the model that estimates the close price returns of Bitfinex on the returns of OkCoin. However, the p-values for the coefficient $\delta_{c,5}$ in the corresponding conditional mean equation is greater than 0.05 implies the close price returns for the Bitfinex and OkCoin exchanges are not significantly different. The p-values for the constant term, $\kappa_{c,5}$, is less than 0.05. Therefore, the Wald test reject the joint null hypothesis of $\delta_{c,5} = 1$ and $\kappa_{c,5} = 0$, with F-statistics value of 2184.84. The same results are shown for the returns that are calculated using the open prices, where most of the conditional variance equations are not stable. The only stable conditional variance equation is the one between the Bitfinex and the OkCoin exchange markets. The p-values of the coefficient, $\delta_{o,5}$, is 0.4026 which is greater than 0.05. This result implies there does not exist arbitrage opportunity between Bitfinex and OkCoin exchange market when the open price is considered. In the following, only the estimated model with stable conditional variance models will be interpreted.

The estimated results from the following conditional mean equations suggest there exist arbitrage opportunities between Bitfinex and CEX.io and HitBTC exchange markets.

$$rh_{1,t} = 0.0004^{(a)} + 0.927^{(a)} rh_{3,t}$$ *Equation 2.6.2.1.1*

$$rh_{1,t} = 0.00007 + 0.990^{(a)} rh_{4,t}$$ *Equation 2.6.2.1.2*

Where (a) indicates the corresponding coefficients are significant at 0.1% level. The p-values for both $\omega_{h,3} = 0.0004$ and $\delta_{h,3} = 0.927$ are less than 0.01 which suggest a strong rejection of the null hypothesis. The F-test statistics for the joint null hypothesis is 212.4 with p-value less than 0.01 which reject the null hypothesis. Results suggest there exist arbitrage opportunity between Bitfinex and CEX.io in the short run. In addition, the coefficient, $\omega_{h,4} = 0.00007$, has p-value of greater than 0.1. But the p-value for $\delta_{h,4} = 0.990$ is less than 0.01

which implies the null hypothesis could not be jointly rejected. The correlation relationship between Bitfinex and the CEX.io exchange market is positively strong. This implies the arbitrage opportunity does not happen very often.

Regarding low price returns, the estimated results from the following conditional mean equations show there exist arbitrage opportunity between Bitfinex and Bitstamp and HitBTC.

$$rl_{1,t} = 0.0016^{(a)} + 0.093^{(a)} rl_{2,t}$$ *Equation 2.6.2.1.3*

$$rl_{1,t} = 0.0016^{(a)} + 0.147^{(a)} rl_{4,t}$$ *Equation 2.6.2.1.4*

Where (a) indicates the corresponding coefficients are significant at 1% level. Results suggest when low prices are considered, the returns between the reference exchange market and the other two exchange markets are weakly correlated. This implies different markets have different tolerance for the falling price. Therefore, this might imply more arbitrage opportunities could be found when the market is experiencing a rapid fall in prices. In summary, when the GARCH(1,1) is considered, only three estimated models with stable conditional variance models reject the null hypotheses.

2.6.2.2. Linear regression with EGARCH(1,1)

The reason to employ EGARCH model is to examine whether there exist asymmetric effect on the news. All the estimated conditional variance models are stable since the coefficients $\alpha_{n,j}$ are less than 1 for n=o, h, l and c. In the following, only the estimated models that reject the following null hypothesis will be discussed:

$$H_0: \omega_{n,j} = 0 \; and \; \delta_{n,j} = 1$$

The $\omega_{n,j}$ represents the constant terms for n=o, h, l, c and j=2,3,4 and 5. The $\delta_{n,j}$ represents the coefficients for the corresponding models using open, high, low and close prices to calculate the returns. Results show lack of evidence supporting the existence of arbitrage opportunity between Bitfinex and the OkCoin exchange market. None of the estimated models reject the null hypotheses when the close price returns are examined.
When open price returns are examined, only the following estimated model reject the null

hypothesis:

$$ro_{1,t} = 0.0009^{(a)} + 1.06^{(a)} ro_{2,t}$$
$$\ln\left(\sigma^2_{o2,t}\right) = -4.09^{(a)} + 0.7^{(a)} * \ln\left(\sigma^2_{o2,t-1}\right) + 0.51^{(a)} * Z_{o2,t-1} + 1.03^{(a)} * \left|Z_{o2,t-1}\right|$$

Equation 2.6.2.2.1

Where the superscripts (a) indicate the corresponding coefficients are significant at 1% level. Results indicate the open price returns between Bitfinex and Bitstamp are not unit linear correlated. They positive correlated on average where a 1% increase in Bitstamp open price return, $ro_{2,t}$, corresponds to 1.06% percent increase in Bitfinex open price returns, $ro_{1,t}$. The result implies price difference between two consecutive periods for these two exchange markets are significantly different on average, where the range of the price difference tends to be slightly greater for the Bitfinex exchange market. The past conditional volatility is persistence with the half-life value of 1.94 which suggest it takes nearly two days to reduce the magnitude of the conditional volatility shock to half of its original size. Although the coefficient, $\emptyset_{o,2} = 0.51$, is positive which suggest positive asymmetric. All the coefficients in the conditional variance equation are significant at 1%, which implies the corresponding EGARCH(1,1) is adequate to employ.

When high price returns are examined, only the following estimated model reject the null hypothesis:

$$rh_{1,t} = 0.00037^{(a)} + 0.92^{(a)} rh_{3,t}$$
$$\ln\left(\sigma^2_{h3,t}\right) = -2.72^{(a)} + 0.79^{(a)} * \ln\left(\sigma^2_{h3,t-1}\right) - 0.09^{(a)} * Z_{h3,t-1} + 0.7^{(a)} * \left|Z_{h3,t-1}\right|$$

Equation 2.6.2.2.2

Results suggest a 1% increase in the high price return of CEX.io, $rh_{3,t}$, corresponds to 0.92% increase in $rh_{1,t}$, which implies there exist price difference regarding intra-day high price between Bitfinex and the CEX.io exchange markets. If ${}^{\varphi_{h,3}}/{}_{\emptyset_{h,3}} < 0$, then negative innovations have higher impact than the volatility on the positive innovations. Given that the coefficient $\varphi_{h,3} = 0.7$ is positive while the coefficient $\emptyset_{h,3} = -0.09$ is a negative value, results suggest there exist negative asymmetric. The Ljung-Box test result for the squared standardized innovation with lag length chosen to be 36 suggest there is no serial correlation. In addition, ARCH test result suggests there is no heteroscedasticity. Note that, price difference between Bitfinex and CEX.io only exist when high price returns are examined.

When low price returns are examined, there are two estimated models that reject the null hypothesis. The following results show there exist price difference between Bitfinex and Bitstamp, not only when open price returns are examined, but also exist when low price returns are examined.

$$rl_{1,t} = 0.0008^{(a)} + 1.06^{(a)} rl_{2,t}$$
$$\ln\left(\sigma_{l2,t}^2\right) = -4.08^{(a)} + 0.68^{(a)} * \ln\left(\sigma_{l2,t-1}^2\right) + 1.44^{(a)} * Z_{l2,t-1} + 2.02^{(a)} * \left|Z_{l2,t-1}\right|$$

Equation 2.6.2.2.3

In addition, the following results suggest there exist arbitrage opportunity between Bitfinex and the HitBTC as expected.

$$rl_{1,t} = 0.002^{(a)} + 0.2^{(a)} rl_{2,t}$$
$$\ln\left(\sigma_{l2,t}^2\right) = -1.43^{(a)} + 0.86^{(a)} * \ln\left(\sigma_{l2,t-1}^2\right) - 0.11^{(a)} * Z_{l2,t-1} + 0.42^{(a)} * \left|Z_{l2,t-1}\right|$$

Equation 2.6.2.2.4

The coefficient $\delta_{l,4} = 0.2$ suggests the low price returns between Bitfinex and the HitBTC has a weak positive correlation on average. The 1% increase in $rl_{2,t}$ corresponds to 0.2% increase in $rl_{1,t}$. The reason for such a big difference could due to the price range at the end of the sample period, where HitBTC tends to have larger price range than Bitfinex. Moreover, ${}^{\varphi_{l,4}}/_{\emptyset_{l,4}} = {}^{-0.11}/_{0.42} < 0$, suggests there exists negative asymmetric effect which implies negative news tend to have greater impact than positive news.

2.7. Conclusion

This chapter only examines the return predictability and arbitrage opportunity in the short run. In terms of Bitcoin return predictability, our findings suggest intra-day price data is useful in predicting the Bitcoin returns. The use of open, high, low and open prices to calculate the corresponding returns lead to different conclusion in market efficiency hypothesis. The close price return does not have any special meaning as it is recorded at 23:45. Also the past close price return cannot predict its current return. The only current price return that could be predicted by its own lag is the high price return. Moreover, there exist another cryptocurrency, Litecoin, whose past return is significant in predicting the current return of Bitcoin. Moreover, the historical yang-zhang volatility estimator is useful in predicting both Bitcoin current return and the conditional current volatility.

In terms of arbitrage opportunity, results indicate arbitrage opportunity does not exist between Bitfinex and OkCoin exchange market. Supporting the previous section that the use of close price returns could reject the efficient market hypothesis. In addition, the use of intra-day extreme data allows seeking for arbitrage opportunity which violates the efficient market hypothesis.

The negative asymmetric effect is significant when intra-day extreme data are used to calculate returns. This makes sense because the intra-day extreme price often reflects on the corresponding news. The negative news has greater impact on the positive news because cryptocurrency is still new to the world compared to the other traditional assets. It does not have intrinsic value just like gold. However, if its capitalization is significantly large with enough liquidity, then it might share similar property as gold such as hedging capability, which will be discussed in detail in the final chapter.

In general, the positive news regarding Bitcoin market is that it is being accepted by some big companies. Note that, here we only mention companies instead of countries because it is assumed that people are free to use Bitcoin until their government announced to ban it or limit its usage. The negative news includes various types. For instance, when a government announces that Bitcoin is not a legal tender or even announce to ban it. Or when Bitcoin platform experiences some technical issue such as forming a fork in the blockchain. Or some exchange markets have been hacked and lost some Bitcoins and so on. Each of the negative news has larger influence than positive news. Therefore, the negative asymmetric effect is expected for the intra-day high, low price returns.

The results suggest Bitcoin is a weak efficient market which supports the previous studies from Alam et al., (2017), Healy (2014), Urquhart (2016), Naidu (2016), Fink and Johann (2014) and Bariviera (2017). However, it is against to the findings from Kurihara and Fukushima (2017) who reject the weak form efficient of Bitcoin market. As this is the first study to examine the arbitrage opportunity among different Bitcoin exchange markets by investigating the price differences among exchange markets. There is not comparison literature. Although this is the first study to examine efficiency across exchanges using price returns. The methodology could be improved to obtain more information. For instance, set a reference exchange market the same way as in this chapter, and run a seemingly unrelated regression equations on all the other price returns and examine the coefficients and conditional covariance among them by from the multivariate GARCH model. Alternatively, one could examine the efficiency across exchange markets more specifically. Since there exist an obvious exponential growth periods of Bitcoin price. One could examine whether such exponential growth periods have the same start and finish day by using a given window length.

2.8. Appendix for Chapter 2

	GARCH	*GARCH-M*	*EGARCH*	*EGARCH-M*
Conditional mean equation				
constant	0.001216***	0.000960*	0.001683***	0.001298***
ro_{t-1}	0.013458	0.012845	-0.017713	-0.019656
σ_t^2	-	2.225853	-	-
$\mathrm{Ln}(\sigma_t^2)$	-	-	-	3.223661
Conditional variance equation				
constant	4.76E-06***	4.70E-06***	-0.753527***	-0.762035***
ε_{t-1}^2	0.220012***	0.219921***	-	-
σ_{t-1}^2	0.803933***	0.804415***	-	-
$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	-	-	0.399869***	0.402547***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.029722	0.031963***
$\mathrm{Ln}(\sigma_{t-1}^2)$	-	-	0.944026***	0.943187***
	R-GARCH	*R-GARCH-M*	*R-EGARCH*	*R-EGARCH-M*
Conditional mean equation				
constant	0.001828***	0.001126	0.001825***	0.011121*
ro_{t-1}	-0.018287	-0.017278	0.022183	0.019804
σ_t^2	-	2.866425	-	-
$\mathrm{Ln}(\sigma_t^2)$	-	-	-	0.001002
Conditional variance equation				
constant	0.000245	0.000244	14.35938***	-14.29753***
σ_{t-1}^2	0.171429	0.171429	-	-
$\sigma_{yz,t-1}^2$	0.000000	0.000000	0.175887***	0.177666***
$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	-	-	0.197969***	0.185451***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	-0.039181	-0.033802
$\mathrm{Ln}(\sigma_{t-1}^2)$	-	-	-0.424332***	-0.415390***

Table 2: AR(1)-GARCH type and AR(1)-Range-GARCH type of models with $ro_{2,t}$ as the dependent variable which is the return calculated using open price. ***, **, * indicate the p-values for the corresponding coefficient which is significant at 1%, 5% and 10% respectively. R-GARCH represents the Range data based GARCH model.

	GARCH	GARCH-M	EGARCH	EGARCH-M
Conditional mean equation				
constant	0.001160***	0.001191**	0.001419***	0.001363***
rh_{t-1}	0.133179***	0.133486***	0.121869***	0.126911***
σ_t^2	-	-0.323465	-	-
$\mathrm{Ln}(\sigma_t^2)$	-	-	-	0.750206
Conditional variance equation				
constant	3.86E-06***	3.85E-06***	-0.605293***	-0.607288***
ε_{t-1}^2	0.181819***	0.181788***	-	-
σ_{t-1}^2	0.826859***	0.826953***	-	-
$\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$	-	-	0.317257***	0.317165***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.055958***	0.056730***
$\mathrm{Ln}(\sigma_{t-1}^2)$	-	-	0.956004***	0.955769***
	R-GARCH	**R-GARCH-M**	**R-EGARCH**	**R-EGARCH-M**
Conditional mean equation				
constant	0.001560**	0.003257*	0.001795***	0.006885***
rh_{t-1}	0.155058***	0.169735***	0.225943***	0.222366***
σ_t^2	-	-8.897960	-	-
$\mathrm{Ln}(\sigma_t^2)$	-	-	-	0.000545
Conditional variance equation				
constant	0.000195	0.000194	-13.89105***	-13.98519***
σ_{t-1}^2	0.171429	0.171429	-	-
$\sigma_{yz,t-1}^2$	0.000000	0.000000	0.153713***	0.155760***
$\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$	-	-	0.077086	0.083828
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.093433**	0.095961**
$\mathrm{Ln}(\sigma_{t-1}^2)$	-	-	-0.378092***	-0.385679***

Table 3: AR(1)-GARCH type and AR(1)-Range-GARCH type of models with $rh_{2,t}$ as the dependent variable which is the return calculated using high price. ***, **, * indicates the p-values for the corresponding coefficient which is significant at 1%, 5% and 10% respectively. R-GARCH represents the Range data based GARCH model.

	GARCH	GARCH-M	EGARCH	EGARCH-M
Conditional mean equation				
constant	0.000912***	0.000454	0.000957***	0.000617*
rl_{t-1}	-0.047205	-0.038524	-0.016247	-0.019877
σ_t^2	-	3.667568	-	-
Ln(σ_t^2)	-	-	-	4.298110*
Conditional variance equation				
constant	9.28E-06***	9.84E-0***	-1.091150***	-1.097267***
ε_{t-1}^2	0.408310***	0.431691***	-	-
σ_{t-1}^2	0.692434***	0.679411***	-	-
$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	-	-	0.555246***	0.569680***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.004797	0.015994
Ln(σ_{t-1}^2)	-	-	0.914953***	0.914906***
	R-GARCH	R-GARCH-M	R-EGARCH	R-EGARCH-M
Conditional mean equation				
constant	0.001725**	-0.001108	0.000913***	0.007805*
rl_{t-1}	0.050193*	0.078767***	-0.007334	-0.052524
σ_t^2	-	10.90214	-	-
Ln(σ_t^2)	-	-	-	0.000695
Conditional variance equation				
constant	0.000258	0.000255	-1.489071***	-1.635062
σ_{t-1}^2	0.171429	0.171429	-	-
$\sigma_{yz,t-1}^2$	0.000000	0.000000	0.006214*	0.007854*
$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	-	-	0.544907***	0.546247***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	-0.010290	-0.006881
Ln(σ_{t-1}^2)	-	-	0.875577***	0.860430***

Table 4: AR(1)-GARCH type and AR(1)-Range-GARCH type of models with $rl_{2,t}$ as the dependent variable which is the return calculated using low price. ***, **, * indicates the p-values for the corresponding coefficient which is significant at 1%, 5% and 10% respectively. R-GARCH represents the Range data based GARCH model.

	GARCH	*GARCH-M*	*EGARCH*	*EGARCH-M*
Conditional mean equation				
constant	0.001337***	0.001020**	0.001389***	0.001024**
rc_{t-1}	0.005906	-0.007008	-0.015731	-0.026153
σ_t^2	-	2.688807	-	-
$\ln(\sigma_t^2)$	-	-	-	3.984363
Conditional variance equation				
constant	5.89E-06***	5.89E-06***	-0.838975***	-0.855371***
ε_{t-1}^2	0.256297***	0.257871***	-	-
σ_{t-1}^2	0.776301***	0.775483****	-	-
$\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$	-	-	0.428837***	0.434542***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.004103	0.008943
$\mathrm{Ln}(\sigma_{t-1}^2)$	-	-	0.936001***	0.934511***
	R-GARCH	*R-GARCH-M*	*R-EGARCH*	*R-EGARCH-M*
Conditional mean equation				
constant	0.001873	-0.000254	0.001422***	0.005987
rc_{t-1}	-0.019083	-0.014920	-0.008674	-0.014019
σ_t^2	-	8.506918	-	-
$\mathrm{Ln}(\sigma_t^2)$	-	-	-	0.000481
Conditional variance equation				
constant	0.000250	0.000249	-1.158432***	-1.169959***
σ_{t-1}^2	0.171429	0.171429	-	-
$\sigma_{yz,t-1}^2$	0.000000	0.000000	0.004847***	0.004998**
$\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$	-	-	0.422281***	0.422795***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.001642***	0.004641
$\mathrm{Ln}(\sigma_{t-1}^2)$	-	-	0.904461***	0.903311***

Table 5: AR(1)-GARCH type and AR(1)-Range-GARCH type of models with $rc_{2,t}$ as the dependent variable which is the return calculated using close price. ***, **, * indicates the p-values for the corresponding coefficient which is significant at 1%, 5% and 10% respectively. R-GARCH represents the Range data based GARCH model.

	GARCH	*GARCH-M*	*EGARCH*	*EGARCH-M*
Conditional mean equation				
constant	0.001072***	0.001248**	0.000981***	0.001361***
rh_{t-1}	-0.380144***	-0.378316***	-0.403615***	-0.393664***
ro_{t-1}	0.180890***	0.181369***	0.187874***	0.200009***
rl_{t-1}	-0.050881	-0.051308	-0.032949	-0.028525
rc_{t-1}	0.684364***	0.685397***	0.704768***	0.694225***
σ_t^2	-	-2.730918	-	-
$\text{Ln}(\sigma_t^2)$	-	-	-	-5.447161
Conditional variance equation				
constant	2.90E-06***	2.85E-06***	-0.732671***	-0.734422***
ε_{t-1}^2	0.196985***	0.198538***	-	-
σ_{t-1}^2	0.817597***	0.817754***	-	-
$\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$	-	-	0.360408***	0.370810***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.032145	0.026668
$\text{Ln}(\sigma_{t-1}^2)$	-	-	0.946889***	0.947480***
	R-GARCH	R-GARCH-M	R-EGARCH	R-EGARCH-M
Conditional mean equation				
constant	0.001071*	0.004871	0.001192***	0.001565***
rh_{t-1}	-0.337964***	-0.318893***	-0.388224***	-0.384349***
ro_{t-1}	0.127618***	0.161309***	0.197446***	0.207630***
rl_{t-1}	0.018703	-0.001367	-0.037886	-0.030035
rc_{t-1}	0.620804***	0.657524***	0.752717***	0.738244***
σ_t^2	-	-29.36817	-	-
$\text{Ln}(\sigma_t^2)$	-	-	-	-5.879851
Conditional variance equation				
constant	0.000138	0.000134	-2.367780***	-2.399400***
σ_{t-1}^2	0.171429	0.171429	-	-
$\sigma_{yz,t-1}^2$	0.000000	0.000000	0.021199***	0.020705***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.126003***	0.119932***
$\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$	-	-	0.318005***	0.330378***
$\text{Ln}(\sigma_{t-1}^2)$	-	-	0.791473***	0.788636***

Table 6: AR(1)-GARCH type and AR(1)-Range-GARCH type of models with rh_t as the dependent variable which is the return calculated using high price. Along with exogenous variables in the conditional mean equations which are the lag of returns calculated using open, low and close prices of Bitcoin.

	GARCH	*GARCH-M*	*EGARCH*	*EGARCH-M*
Conditional mean equation				
constant	0.001139***	0.001177**	0.001467***	0.001434***
rh_{t-1}	0.114880***	0.115226***	0.103562***	0.102881***
lrh_{t-1}	0.051919**	0.051938**	0.051288**	0.051277**
σ_t^2	-	-0.391817	-	-
Ln(σ_t^2)	-	-	-	0.396062
Conditional variance equation				
constant	3.88E-06***	3.87E-06***	-0.611964***	-0.611924
ε_{t-1}^2	0.182397***	0.182324***	-	-
σ_{t-1}^2	0.825928***	0.826073***	-	-
	-	-	0.318734***	0.318468***
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.053836***	0.054034***
Ln(σ_{t-1}^2)	-	-	0.955498***	0.955480***
	R-GARCH	R-GARCH-M	R-EGARCH	R-EGARCH-M
Conditional mean equation				
constant	0.001480**	0.003115	0.001749***	0.005918
rh_{t-1}	0.121286***	0.135048***	0.204388***	0.203573***
lrh_{t-1}	0.080569***	0.078139***	0.05503***	0.054500**
σ_t^2	-	-8.681528	-	-
Ln(σ_t^2)	-	-	-	-0.000447
Conditional variance equation				
constant	0.000192	0.000191	-13.76442***	-13.83978***
σ_{t-1}^2	0.171429	0.171429	-	-
$\sigma_{yz,t-1}^2$	0.000000	0.000000	0.082259**	0.087924**
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-	-	0.081462***	0.083291***
Ln(σ_{t-1}^2)	-	-	-0.365323***	-0.371446***

Table 7: Granger causality test.

Chapter 3

3.1. Introduction

There exists more than thousands of cryptocurrencies in the world. Different cryptocurrencies operate according to their own protocols which were set when they were first created. Such protocols could be amended if more than 50% of the nodes (users) agree to make a change in the protocol. Differences in these protocols differentiate one cryptocurrency from another. For instance, Zerocash extends Bitcoin protocol in order to reveal neither payment source, receiver information nor the amount of transaction for each transaction. Such feature allows Zerocash user to preserve their privacy better than Bitcoin via collecting and verifying payment information differently. Each cryptocurrency could choose between proof of work and proof of stake process which changes the way that miners receive their rewards after solving mathematical problems. Bitcoin uses proof of work where a predetermined number of new Bitcoins will be generated for every ten minutes on average. Miners who solve the mathematical problem and join a block into the blockchain will be rewarded for some Bitcoins. Other cryptocurrencies such as Ripple, which uses proof of stake also require miners to solve the mathematical problem to validate the transactions. But miners receive transaction fee instead of newly generated cryptocurrency as a reward because this type of cryptocurrencies is pre-mined. The transaction fee that miners receive is based on the amount of Ripples the hold in their account. The proof of stake process allows less energy to solve the mathematical problem. Since Ripples were pre-mined, the foundation received a large portion of Ripples. Nowadays, many banks corporate with Ripple and control the payment within Ripple system. Therefore, it is said that Ripple is not as decentralized as other cryptocurrencies such as Bitcoin. However, an advantage of Ripple is that it could handle a large volume of transactions with quicker speed and lower transaction cost when compared to Bitcoin. Also, transactions could be monitored by these banks so that illegal transactions are difficult to occur. Another cryptocurrency called Ethereum uses blockchain technology to provide a platform for users to run their projects via smart contracts. Therefore some decentralized applications could be operated via Ethereum platform. Within the Ethereum network, Ethereum acts like a token for users to purchase goods and services. Therefore, unlike Bitcoin, Ethereum is more than a currency or asset. Another cryptocurrency, Bitshares was known as a smart coin is pegged its value to another asset such as US dollar just like other smart coins. Its main feature is to provide a platform for users to trade assets such as gold, cryptocurrency, fiat currency, commodity and so on without a third party to exist. Therefore, only a small fee is required for each transaction, and it's more reliable than other cryptocurrency exchange markets such as Mt. Gox and Bitstamp. The above discussed cryptocurrencies use different codes to Bitcoin and serve different purposes as Bitcoin. The purpose of this chapter is to investigate the dynamic relationship of two cryptocurrencies. One of the selected cryptocurrency is Bitcoin because it is the first decentralized cryptocurrency which has the largest market capitalization. The secondly selected cryptocurrency is Litecoin because it is a fork of Bitcoin which was created based on Bitcoin codes but uses different protocols as Bitcoin. For instance, it uses different hashing algorithm which allows miners to mine Litecoin quicker and more efficient. For the last new years, Litecoin has always been one of the five largest cryptocurrencies regarding market capitalization. Up to the date of writing this thesis, Litecoin ranks the fifth place in terms of market capitalization which is after Etherum, Ripple and Bitcoin Cash which is another form of Bitcoin. More than 90% of cryptocurrencies were created based on Bitcoin. Therefore understanding the behaviour of this kind of cryptocurrencies and their relationship is important for the investor who considers cryptocurrencies in their investment portfolio.

The remainder of this chapter is divided into seven sections. First, previous studies in the related field will be discussed. After reviewing previous studies, the motivation and research questions for this chapter will be discussed. Thirdly, related methodology approaches will be discussed. Then, the collected data will be analyzed followed by the introduction of the estimated model and hypotheses expectation for the results. Then results will be analyzed following by a discussion of the implication of results.

3.2. Literature review

There are mainly four research areas for cryptocurrency. The first area focuses on the technology side includes cryptographic problem, mining process, network security and transaction within the blockchain (Eyal and Sirer, 2014). Blockchain is a technology that every cryptocurrency uses and it could avoid double spending problem along with the decentralization feature. Furthermore, it could extend cryptocurrency into a platform which allows wider range of applications which are known as decentralized applications. Many papers studied the challenges, limitations and the future directions of blockchain technology. Yli-Huumo et al., (2016) analyzed 41 primary papers from this topic and showed that 80% of the papers focus on Bitcoin system while the rest of 20% study other blockchain applications such as smart contract. Most of the papers focus on finding the limitation and the ways to improve the blockchain technology from privacy and security perspectives. The second area discusses the regulation of cryptocurrencies such as taxation and anti-money regulations (Androulaki, 2013). There has been a concern on the use of Bitcoin for illegal activity due to Bitcoin properties such as decentralized and anonymous (Barratt, 2014). Franklin and College (2016) examine some literature on Bitcoin and discuss the issues of Bitcoin and suggest Bitcoin is lack of regulation, banks and governmental control. It is shown that each country has different regulation on cryptocurrency. Some regulations stimulate the use of cryptocurrencies but some regulations suppress cryptocurrency. The cryptocurrency started draw the world's attention in 2013 and it is still growing fast. Therefore, some of the law and regulations in many countries have not caught up the growth of cryptocurrency. Turpin (2014) suggests governments should study Bitcoin regulation and be open to business who uses cryptocurrencies appropriately and take action for illegal use of cryptocurrencies. The third area relates to three aspects including sociology, ethical and political. Dodd (2017) argues that if Bitcoin becomes a form of money, then it cannot succeed in its own terms as an ideology because money must be abstracted from social life and money is controlled by the intermediaries and political authorities. The final area focuses on economic issues (Polasik et al., 2014). Different topics in this area have been discussed such as examining whether Bitcoin has the potential to be the currency that can compete with fiat currency or does it act more like an alternative asset when comparing to traditional assets. The volatility of Bitcoin is much higher than many commodities, fiat currencies or other investment assets. There are some studies examine the volatility of Bitcoin price. Furthermore, researchers try to find some determination factors for Bitcoin price given that the Bitcoin nature is different to most commodities for instance the supply of total Bitcoin are predetermined at an exponential decay rate. Even though Bitcoin has the largest cryptocurrency market share, some researchers rise some interesting questions on competition issue and analyze the relationship among cryptocurrencies. They also try to find out whether arbitrage opportunities exist among these cryptocurrencies in different exchange markets.

3.2.1. Currency or Asset

Being the first decentralized cryptocurrency, Bitcoin has drawn many attentions from the media and researchers. Like other cryptocurrencies, Bitcoin has similar features as fiat currency. However, due to its volatility, many studies discuss whether Bitcoin behaves like a currency or it can be treated as an asset. Either Bitcoin as a currency or as an asset would have an impact on Bitcoin system. Both theoretical and empirical studies on this topic have been done, and mixed evidence was concluded.

Luther (2013) suggests private digital currency with a function of money for Somalia will circulate in the network for some time. Baur (2015) compares the value of Bitcoin with different assets and found investors who treat Bitcoin as an asset and are holding a third of total circulated Bitcoins.

Yermack (2013) analyzes the change of Bitcoin price against fiat currencies and concludes that Bitcoin as an asset since it does not fulfil the function of currency due to its volatility. Bouiyour and Selmi (2014) analyze the relationship between Bitcoin price and transaction volume and investors' attractiveness respectively. They conclude that Bitcoin does not behave like a currency. Florian (2014) analyzes the property of Bitcoin by examining the change of Bitcoin network transaction volume and exchange market volume. He argues that if users treat Bitcoin as a form a currency, then Bitcoin will be spent on services or goods soon after they have purchased from the exchange. If users treat Bitcoin as an alternative investment asset, then the level of new register Bitcoin users should not affect the Bitcoin network volume. The result of this empirical research suggests Bitcoin is treated as alternative investment asset rather than a currency. Another empirical research from Cheah and Fry (2015) suggests the same result.

Gandal and Halaburda (2014) examine the property of Bitcoin by examining network effect of Bitcoin system for two different periods. They argue that more users adopt Bitcoin as a currency then the more people use Bitcoin the strong the network effect within the Bitcoin system. Hence the price or market share for Bitcoin will grow significantly compared to the rest of the cryptocurrencies. In total, three sample periods were examined including the whole sample period and two sub-sample periods split from the whole sample periods. Results suggest Bitcoin behaves like currency for a sub-sample period but behaves like an asset for another sub-sample period. Hence, they could not get uni-direction results from this sub-sample which implies the relationship is unstable. They found out Bitcoin is a good option for a diversified portfolio due to its lower correlation with other assets and high average of returns.

3.2.2. Factors Determination

3.2.2.1. Macroeconomic theory

In many monetary theories, some factors play an important role when determining the price level of currency. These factors are the supply and demand for the currency, interest rate and rates for inflation, tax, wage and unemployment. Some developed monetary theories include fiat debt-free money, modern money, post-Keynesian reformer, social credit reformers and competing for currency reformers (Georgoula et al., 2015). Several models were suggested in determining the value of the currencies. However Bitcoin price cannot be explained by classic economic theories since the supply and demand for fiat currencies are different for cryptocurrencies. Bitcoin is decentralized which suggests standard monetary policy would not affect Bitcoin price. Also, the supply for Bitcoin is limited to 21 million Bitcoins, and it is generated at a predetermined rate. As the results of many studies have shown above, the demand for Bitcoin is driven by investor's behaviour. There is no interest rate for Bitcoin network compare to fiat currencies, where the central bank will provide interest rate for fiat currency, and the interest rate term structure can be achieved from government bonds with different maturities. Therefore profits can only be earned from the change of Bitcoin price rather than holding it for some time. Therefore monetary models that are related to interest rate do not have much meaning for cryptocurrencies. The Bitcoin price is not affected by macroeconomics fundamentals such as interest rate and inflation rate (Kristoufek, 2013). Geogoula et al. (2015) also state Bitcoin price is purely determined by supply-demand fundamental, and it is not pegged against any fiat currencies. Kristoufek (2013) argues that Bitcoin market is dominated by short-term investors and speculators because the demand for

Bitcoin is not affected by the expected macroeconomic development within the Bitcoin economy. Instead, the demand is only driven by expected profits for holding Bitcoin for a period of time and sell it at a higher price.

3.2.2.2. Media and search engine

Bitcoin was only known to a few people until the event of Cyprus crisis in 2013 which has drawn lots of attention from the global media after that. Many researchers found out the effect of social network and search engine on Bitcoin price is striking. Therefore many studies have used search volumes from Google, Wikipedia and Tweeter to examine the behaviour of Bitcoin price. Given the structure of these data, the frequency of Google and Wikipedia searches are weekly and daily data respectively. Both of these measurements provide an overview of weekly and daily hits on searching Bitcoin-related topics. They could be used to represent the number of uninformed users who are fairly new to Bitcoin and have limited knowledge about Bitcoin (Wang, 2013). However, daily data for Wikipedia views could provide more details about the behaviour of Internet users for statistical analysis. If search traffic affects Bitcoin network transaction, then it shows new users treat Bitcoin as a currency. If search traffic affects exchange market volume instead, then it could indicate Bitcoin has attracted investors (Florian, 2014). Either new users treat Bitcoin as a currency or an asset will have an impact on Bitcoin price.

Gandal and Halaburda (2014) discovered the main determinants for Bitcoin price include sentiment expressed in the cryptocurrency report and transaction volume. They split the sample period into two sub-sample periods because they believe there is a natural break in the data in October of 2014. For the first sub sample, they compare the popularity of Bitcoin with other cryptocurrencies based on their exchange rate against US dollar. For the second period, they employed the Google trend variable to examine the popularity among cryptocurrencies. They found Google search for Bitcoin is always higher than other cryptocurrencies, but the percentage changes the in a number of Google search for other Litecoin and Peercoin are higher than Bitcoin. They used Johansen test to test the cointegration between engine search series and Bitcoin price and found there exist cointegration between Wikipedia view series and Bitcoin price series while there is no cointegration relationship for Google Trend series (Google series) and Bitcoin price series. They have transformed Google series, Wikipedia view series and Bitcoin price series into logarithmic form and employed Vector autoregression (VAR) methodology for Google series and Vector error correction model (VECM) for Wikipedia series. Based on information criteria, the optimal lag lengths they have chosen for VAR and VECM models are 1 and 7 respectively. Results were statistically significant for both models. However, they argued the downside of using such search series is difficult to distinguish whether the corresponding search was due to positive/negative effect because researches during increasing trend and bubble burst have a different effect on Bitcoin price. Therefore they let a dummy variable to be 1 if Bitcoin price is above the trend line and 0 if below the trend line. They conclude positive and negative feedbacks are symmetric around zero which means the reaction magnitude for both types of feedbacks are similar, the only difference is the sign.

Other studies have also shown there exist a strong link between Bitcoin price and search queries. For instance, Florian (2014) suggests using web resources such as Wikipedia which will help to determine the Bitcoin price. Kristoufek (2013) examined both weekly Google trend and daily Wikipedia series in the relationship with Bitcoin price. All three series are transformed into logarithm form. Results show the correlation between Google trend and Bitcoin price is 0.8786 which is similar to the correlation between Wikipedia and Bitcoin price which have a value of 0.8271. Given the results are similar, it might be better to use Wikipedia series because it has a higher frequency and provides more details of the behaviour of users who search for Bitcoin on Google and Wikipedia websites. Therefore, a more precise statistical analysis could be given for Wikipedia view series rather than Google trend series. Kristoufek (2015) shows the part of the Bitcoin price during the bubble and burst cycle could be explained by Google and Wikipedia search queries. Based on economic theory, the ratio between trade and exchange transaction volume was used to examine the demand for Bitcoin which was used to find the relationship between demand and price for Bitcoin. It was found that price leads the ratio in the short run in the way that increases in price boost the exchange transaction volume in the short run. Here, the increase in Bitcoin is seen as a potential bubble which is caused by the increase in demand in Bitcoin at exchange markets. Results suggest during the bubble and burst cycle, the interest of Bitcoin has an asymmetric effect on Bitcoin price. For instance, during the bubble formation period, the interest will stimulate the Bitcoin price while during the bursting period interest will lower the price. EIBahrawy et al., (2017) use weekly data to examine the long-term relationship among cryptocurrencies. Their findings suggest Bitcoin capitalization grows at an exponential rate. Note that Bitcoin capitalization is calculated by multiplying Bitcoin price and the quantity of Bitcoin in the circulation. Since the number of newly generated Bitcoin changes at exponential decay rate for roughly every four years. Therefore, it could be seen that Bitcoin price is growing at an exponential rate which suggests Bitcoin did not experience a bubble in 2014 like Kristoufek (2015) mentioned. As a social network platform, Tweeter allows users to communicate with each other and show one's sentiment on cryptocurrencies. This feature could improve the weakness from both Google and Wikipedia search queries on predicting Bitcoin price. Georgoula (2015) examine whether Tweet's sentiment will affect Bitcoin price. Series of eleven variables were collected and transformed into logarithm form. These variables include daily closing Bitcoin price from Bitstamp exchange as the dependent variable, number of Bitcoin circulated in the network represent the total money supply, Bitcoin money velocity, daily exchange rate between US dollar and euro which represent the global economy, stock market index, level of mining difficulty that is captured by the has rate to represent the processing power of the network, Google trends, Wikipedia search, number of twitter posts and at last the daily sentiment ratio related with Twitter posts. He used ordinary least square (OLS) to regress these variables on the log of Bitcoin price and employed VECM for cointegrated series. The OLS results show strong evidence on the correlation between interest and Bitcoin price. Specifically, there exist positive effect on Bitcoin price from Wikipedia views, hashrate and sentiment ratio in the short run while the USD/EUR exchange rate has a negative effect. The first part of the Vector Error Correction Model (VECM) shows the short run relationship and the speed of adjustment to the long run equilibrium which involves four lags of the log of Bitcoin price, log of stock of Bitcoin, log of S&P's 500 indexes and the log of USD/EUR exchange rate variables. The second part contains a cointegrating equation which involves logarithm form of stock of Bitcoin, S&P's 500 indexes and USD/EUR exchange rate. The coefficients from the cointegrating equation suggest an increase in the stock of Bitcoin and S&P's 500 stock index will lead to increase and decrease in Bitcoin price in the long run. Chu and Nadarajah (2015) state the strongest impact on Bitcoin price can be captured by these variables which could indicate the attractiveness for investors.

3.2.2.3. Transaction

Transaction factor is one of the important determinant factors to be considered in analyzing Bitcoin price. It includes transaction cost, transaction volumes for both Bitcoin network and exchange market and the size of supply-demand for each transaction. In this paragraph, the transaction volume refers to the transaction taken place within the Bitcoin network while the trading transaction volume refers to the transaction taken place among different exchange markets. Even for cryptocurrency market, the size of transaction volumes will affect the liquidity of trading market which will influence the trading price. However many Bitcoin studies have been using transaction volume and trading transaction to measure the size of Bitcoin usage in order to examine the property of Bitcoin (Polasik, 2014). Georgoula (2015) considers the total number of Bitcoin transaction within the network as the size of Bitcoin economy. Kristoufek (2015) argues the trading transaction will be positively related to Bitcoin price since there will be an increased usage of Bitcoin and cause an appreciation of Bitcoin in the long run. Gandal and Halaburda (2014) argue the transaction volume is an important factor to consider Bitcoin price. Chu and Nadarajah (2015) state there is no bid-ask spread for Bitcoin price since there is no intermediary. Bid-ask spread is frequently to be treated as the main determinant factor for transaction cost. Therefore with the absence of transaction costs of trading Bitcoin in cryptocurrency exchange market, there will be an influence on the movement of Bitcoin price and statistical property of Bitcoin return data. There is a significant amount of studies claiming the effect of transaction costs and bid-ask spread on the price of returns (REF). Chu and Nadarajah (2015) suggest the transaction costs will affect investor behaviour and lead to an impact on Bitcoin price. Kristoufek (2015) states a negative relationship between transaction cost and Bitcoin exists.

3.2.2.4. Technical factors

New Bitcoins are generated through mining process by miners at a predetermined rate which is set by Bitcoin protocol. Miners are mining Bitcoins by offering their computational power and electrical power through mining device. Since the Bitcoin has drawn media's attention, more miners join the network in order to gain profit out of it. The technology of mining developed significantly as the mining device become more advanced. As the number of miners increase, more miners are competing with each other to achieve the Bitcoin rewards. Therefore the mining difficulty increases since the Bitcoin rewards are generated roughly every 10 minutes. The difficulty can reflect the computational power and number of mining competitors which becomes a measurement of Bitcoin system productivity (Kristoufek, 2015). Many of current Bitcoin transactions would include transaction fee for miners in order get the first confirmation even quicker as more miners are willing to include the corresponding transaction records into a new block and solve it through a mathematical algorithm. Kristoufek (2015) observes the relationship between Bitcoin price and both mining difficulty and hashrate. He found a positive correlation in the whole sample period between 14/Sep/2011 and 28/Feb/2014 which suggest the increase of Bitcoin price attracts more miners to join mining process for rewards. But the correlation becomes negatively correlated for the period after November of 2013 because the Bitcoin price started to fall in November of 2013. Therefore, the Bitcoin price becomes less attractive to new miners to join the mining process. At the same time, existing miners might leave the mining process due to the high cost of computational power.

3.2.2.5. Other drivers

Brandvold et al. (2015) suggest there are other important factors that can affect the Bitcoin price. For instance, by influencing the behaviour of investors such as uncertainty risk for Bitcoin system, market size and transaction fee which is received by miners during the Bitcoin payment. Van Wiik (2013) found evidence that Dow Jones index, US dollar and euro exchange rate and oil price have a significant effect on Bitcoin price in the long run. Kristoufek (2014) examine the relationship between Bitcoin price and both financial stress index and gold price in a stable currency, Swiss franc. Results show Bitcoin price is not positively correlated with these factors and conclude Bitcoin is not a safe haven due to the volatility of Bitcoin price at that time.

This section covers what has been done so far on the factor determination from the previous studies. In the section, most of the studies conclude transaction volume, search engine and hashrate are important factors in determining Bitcoin prices because Bitcoin price is only driven by supply and demand factors. Given that the supply of Bitcoin and most of the other cryptocurrencies are fixed and generated at a predetermined rate. Therefore these three factors will be used to consider the demand side of cryptocurrency in this chapter for analysis. Most of the previous studies have been using these factors to examine the Bitcoin price, and not many studies have used these factors for explaining the returns of cryptocurrencies. Moreover, no study has examined whether any of these factors in one cryptocurrency could affect the returns of another cryptocurrency. The following section review what findings have been found regarding the volatility of cryptocurrencies' returns.

3.2.3. Volatility

Forbes journalist claims its high volatility could be explained by the uncertainty of its value in the long run. People are still at the stage of experimenting how useful Bitcoin is. Williams (2014) claims Bitcoin price has volatility seven times, eight times and eighteen times greater than gold, S&P 500 and U.S. dollar respectively. Some ideas were proposed to help to reduce the volatility of Bitcoin. For instance, changing the Bitcoin protocol so that Bitcoin algorithm contains a feedback loop such that if Bitcoin price increase then more Bitcoins will be generated and given a reward to miners (Buterin, 2013). Some investors consider Bitcoin as an investment asset in their portfolio due to its volatility and independent property with other assets. Most of the current literature investigate how Bitcoin volatility behaves and its relationship with Bitcoin return. Only a few studies examined the volatility of Bitcoin price between different exchange markets.

Nathnalie and Malin (2014) employ AR(1)-GARCH(1,1)-Mean model with several explanatory variables in the mean equation to examine the volatility of Bitcoin return by using daily data between 13/09/2011 and 03/05/2014 collected from Bitstamp exchange. They identify both trading volume and the number of online search queries have positive effects on Bitcoin price. The significant negative effect of trend variable in the mean equation suggests an increase in acceptance of Bitcoin will reduce the Bitcoin volatility.

Balcilar et al., (2016) examine whether trading volume could be used to predict Bitcoin return and volatility by using daily data of trading volume and Bitcoin price between 19/12/2011 and

25/04/2016. Using two causality-in-quintiles tests that based on VAR(7) model with Bitcoin return as the dependent variable. The first test considers the linear relationship between volume and returns as well as volatility. The second test considers non-linear relationship which confirms reliance on non-parametric quantile-in-causality method. With consideration of a structural break within the examined period, results found volume could be used to predict Bitcoin return in two sub-periods but not volatility for the whole examined period. In addition, causality-in-quantiles test was employed with consideration of GARCH-based estimate of volatility. Results suggest volume could predict volatility over the whole sample period.

Bouri et al., (2016) examine the relationship between Bitcoin return and volatility around price crash in 2013. Daily Bitcoin price was collected in terms of six fiat currencies such as American dollar and euro between the period of 18/08/2011 and 29/04/2016. Asymmetric exponential GARCH model was estimated for the whole sample period and two sub-periods. Results suggest asymmetric terms is positively related in the first period before the crash and concluded volatility asymmetry is not affected by the estimated model. Furthermore, by using the estimated volatility from GARCH model, optimal portfolio weights were calculated for US equities (S&P 500) and Bitcoin. Results suggest Bitcoin could reduce risk effectively.

Baur and Dimpfl (2017) collect Bitcoin prices from 6 different exchange markets in terms of US dollar, Chinese Yuan and Euro for the period between 01/01/2014 and 25/01/2017. The realized variances and covariance for exchange markets were calculated by using the five-minute interval of intra-daily percentage return. Then VAR of log realized volatility and the log of trading volume for each market was estimated. Granger causality results suggest realized volatility Granger cause volume, but volume does not Granger cause volatility.

Qu (2017) examined the volatility transmission of Bitcoin price between Chinese and US markets by using daily data between 08/05/2015 and 30/09/2016. Bitcoin prices in both Chinese and US exchange markets were obtained as well as exchange rates of Chinese Yuan and US dollar so that Bitcoin prices are being compared with the same currency. The VAR(1)-MGARCH(1,1)-BEKK model has been employed to analyse the volatility transmission of Bitcoin price between Chinese and US cryptocurrency exchange markets. Given that cointegration relationship was found between Bitcoin prices in China and US markets at 10% significant level. Qu included error correction model and changed VAR into VECM model. Results only found significant volatility transmission from US Bitcoin market to Chinese Bitcoin market at 5% significant level.

Some studies examine the statistical properties of cryptocurrencies and compare the Bitcoin volatility with other cryptocurrencies' volatilities. Osterrieder (2017) examines statistical properties of the seven most important cryptocurrencies including Bitcoin and Litecoin which is regarded as Bitcoin's leading rival. Daily data was for the period between 23/06/2014 and 28/02/2017 which excludes the volatile period at the end of 2013. Results suggest cryptocurrencies have different distributions. The generalized hyperbolic distribution gives the best fit for Bitcoin and Litecoin. In addition, Osterrieder et al., (2016) compare the volatilities and correlation of Bitcoin and Litecoin by using annualized standard deviation of returns and Pearson's correlation coefficient for daily data between 23/06/2014 and 30/09/2016. Results suggest Litecoin is more volatile and it has a positive correlation with Bitcoin with Pearson's correlation coefficient closed to 0.6.

Parlstrand and Ryden (2015) examined the statistical properties of Bitcoin, Ripple and Litecoin using ordinary least square method. Each of these has different hash algorithm and protocols. Results suggest Google trend index has significant impacts on cryptocurrencies. The prices of cryptocurrencies do not depend on their own volatility.

Haferkorn and Diaz (2015) examined the payment behaviour for Bitcoin, Litecoin and Namecoin and whether the quantity of payments is interconnected among these cryptocurrencies. Results suggest strong weekday seasonality could be found in Bitcoin but weak and no seasonality for Litecoin and Namecoin respectively. Furthermore, there was no interconnected relationship.

Only a few studies have used multivariate GARCH model for examining volatility dynamic relationship of returns between Bitcoin and another asset. Most of the existing studies relate return of Bitcoin with traditional assets such as fiat currency, stock index, bond and so on. No study has been found to examine the returns between Bitcoin and Litecoin. Moreover, this study extends previous studies by including a few exogenous variables so that vector autoregressive model with exogenous variables methodology will be used. In addition to the GARCH terms in conditional variance covariance models, the GARCH terms will also be considered in the conditional mean models such that volatility transmission could also be examined in the mean equations.

3.2.4. Competition

This section review the previous work on examining the relationship between Bitcoin and other cryptocurrencies. Some studies examined the competition among cryptocurrency markets by analyzing the behavior of cryptocurrency prices in different sample periods. Dwyer (2014) showed Bitcoin and other cryptocurrencies can co-exist as long as there exists exchange rate among them. Bornholdt and Sneppen (2014) show Bitcoin does not have special advantage over the rest of the cryptocurrencies and it is possible for another cryptocurrency to replace Bitcoin. Gandal and Halaburda (2014) consider the network effect and examine the competition of Bitcoin with other cryptocurrencies in order to observe the change of cryptocurrency prices. The examined cryptocurrencies include Bitcoin, Litecoin, Peercoin, Namecoin, Feathercoin, Novacoin and Terracoin with daily data between 02/05/2013 and 28/02/2014. They analyzed the data in two different time periods with threshold date being 30/09/2013. By examining the correlation between Bitcoin and other cryptocurrencies, they found the first period show a winner-take-all effect is dominant for Bitcoin which means Bitcoin become more valuable against US dollar and other cryptocurrencies. Some of the cryptocurrencies lose their values and failed to operate anymore. Litecoin, Peercoin and Namecoin maintain their values against Bitcoin over time. Briere et al. (2013) found the similar results as Gandal and Halaburda. The second period shows substitution effect is dominant indicating values for other cryptocurrencies increase at a quicker rate than Bitcoin against to US dollar. Results suggest substitution effect increase the demand for other cryptocurrencies when Bitcoin price is high and volatile. This effect could be explained by the protocol differences between Bitcoin and other cryptocurrencies. They employ a VAR model for two different periods and examine these two period have different currency movements. Both differenced of returns of Litecoin/Bitcoin and USD/Bitcoin were regressed on their lag terms. Causality test suggest neither lag terms in the differenced of exchange rates predicts the differenced of current exchange rates in the first period. However, cross-lag terms could predict the differenced of current exchange rates in the second period. Results suggest there exist direct competition between Bitcoin and Litecoin in the second period. In consistent with correlation data, Granger causality test results also suggest there are more interaction between cryptocurrencies in the second period. Only a few studies have examined the relationship between the returns of Bitcoin and other cryptocurrencies. None of them has taken volatility into account for analysis. Moreover, their sample periods are before the year of 2014 which need to update to longer sample period so that more information on investors' behavior on cryptocurrency could be obtained.

3.3. Motivation

As a medium of exchange and store of value, people can use Bitcoin to purchase any goods and services that could also be purchased by fiat money such as US dollars. Bitcoin could be used to purchase any products online even though some websites do not accept Bitcoin. This kind of payment could happen through a third party website which accepts Bitcoin as payment method and Bitcoin is handled by the website itself. Many e-commerce websites have accepted Bitcoin including Microsoft, Amazon, eBay and so on. More merchants are accepting Bitcoin as payment method due to its irreversible property, which will be discussed later. Apart from the online store, more physical stores such as retail store and restaurants are accepting Bitcoin. Any businesses, either the online store or retailing store could accept Bitcoin as a payment method at a low cost. They are only required to have a computer, tablet or smartphone, which has a Bitcoin account and software in it. However, if they were handling Bitcoin themselves, then they would have to take into account of its volatile property. Otherwise, they could choose to use a third party processor which can exchange Bitcoin into fiat money for merchant instantaneously. However, this will usually need the merchants to pay some fees for each transaction they make or sign a contract with the third party to pay a certain amount of fees over a period of time. There exist a relative price between cryptocurrency and fiat currency because cryptocurrencies such as Bitcoin could be used to purchase the same kind of products and services as by using fiat currency such as US dollars.

Therefore cryptocurrency such as Bitcoin has a function of money. Moreover, since Bitcoin is not the only cryptocurrency. It is interesting to examine how Bitcoin relates to other cryptocurrency. Is there a dynamic relationship between Bitcoin and an alternative cryptocurrency? Do they react to the same types of factors? Does it exist spillover effects between these cryptocurrencies? The following of this chapter will be looking into the behaviour of cryptocurrencies and the dynamic relationship between Bitcoin and another alternative cryptocurrency.

Most of the previous studies that examined Bitcoin volatility used different approaches and different sample periods. Some of them considered exogenous variables and examined the Granger causality relationship among Bitcoin return, volatility and exogenous variables. Only a few studies examined the Bitcoin price volatility transmission. This type of literature could be classified into two categories. One group of these studies examine the volatility transmission of Bitcoin price among different Bitcoin exchange markets. The other group of studies examine the volatility transmission between Bitcoin and other traditional assets or alternative investments. None of the literature investigates correlation of Bitcoin with another one cryptocurrency with consideration of volatility. In addition, no literature tried to construct an optimal portfolio only include cryptocurrencies.

As Bitcoin was the first decentralized cryptocurrency, it gains lots of attention from the world. However, no one can ensure the future of Bitcoin. For example, if Bitcoin mining process becomes too inefficient which is consuming too much electrical power and start to have an impact on the environment. In this case, a cryptocurrency with more efficient mining process might be preferable. There are other examples which show Bitcoin protocol is not perfect. For example, Bitcoin uses proof-of-work protocol so that miners contribute their computational power to mine newly generated Bitcoin as their rewards. Under such a protocol, the Bitcoin network is vulnerable under 51 attack which means if some organizations are contributing more than 50% of the total computational power. Then such organizations could double-spend their Bitcoin or reverse some transaction. At the current time, it is unlikely that such attack will appear because there are many miners securing the network. It will not be worthy for any organization to contribute so much computational power on attacking the network.

However, as technology develops it is possible that quantum computing technology will be added into mining machine. In that case, it will be economically possible for some organization to execute 51% attack on the network. If the time comes, then Bitcoin network will be vulnerable again.

Bitcoin is not only a digital currency. It is also a technology which provides blockchain technology consisting decentralized feature in order to solve the double spending problem. Most of the existing cryptocurrencies also have the decentralized feature. Almost every cryptocurrency uses blockchain technology for different purposes. Therefore, even if Bitcoin collapses, such technology is unlikely to vanish. So would another cryptocurrency take its place and dominate the market? If Bitcoin continues to dominate the market, would other survived cryptocurrencies interact with Bitcoin? This study focus on the latter situation. It fills in the literature gap by examining the relationship between Bitcoin and the second largest cryptocurrency, Litecoin.

The main purpose of this study is to investigate the dynamic relationship between Bitcoin and Litecoin returns. With the reasons given in section 3.1 and the information provided in the literature review section. Litecoin is concluded to be more suitable for examining along with Bitcoin in this study. The main reason is that Litecoin is another fork of Bitcoin whose codes are based on Bitcoin but changed some of the protocols. Litecoin was invented for higher efficient mining, and its purpose is the same as Bitcoin. Therefore Litecoin is different to other cryptocurrencies such as Ripple and Etherum who were created as a token for a specific platform (details were given in the introduction section). This study fills in the gap of literature in three ways. First, to examine both mean and volatility between Bitcoin and Litecoin and understand how shocks and volatility are transmitted between Bitcoin and Litecoin. Multivariate GARCH model would be employed. Secondly, exogenous variables would be included in the bivariate vector autoregressive model so that the effects of exogenous shocks on both Bitcoin and Litecoin returns could be examined. Majority of previous studies have found these exogenous variables has a significant effect on Bitcoin returns. However, no literature has examined the cross effect of different cryptocurrencies. Thirdly, by constructing the suitable model to estimate conditional volatility dynamics between Bitcoin and Litecoin and conditional covariance between these two cryptocurrencies. An optimal portfolio for cryptocurrencies could be built by computing the optimal weights of these two cryptocurrencies. An investor might want to include cryptocurrency in their portfolio because there exists growth potential in cryptocurrency prices, but at the same time, they might be afraid of the volatile properties of cryptocurrencies. A diversification portfolio of cryptocurrencies might help to reduce risk while maintaining a certain level of returns. This chapter uses the bivariate form of GARCH model. More specifically, the BEKK model will be employed in order to examine the dynamic relationship between Bitcoin and Litecoin markets. This model can capture the volatility transmission between two markets.

3.3.1. Research questions

Ever since the invention of Bitcoin, many other cryptocurrencies have been created. Along with Bitcoin price raise in 2013, prices for many other cryptocurrencies have also increased significantly since their creation dates. Some studies show Bitcoin behaves like a leader in cryptocurrency and dominate the market for a period of time and behaves like a follower for another period of time. Therefore the behaviour of Bitcoin users or investors on Bitcoin market varies for different periods of time. If Bitcoin is the market leader and investor could obtain a high return from Bitcoin market, then Bitcoin will attract more investors and miners into the cryptocurrency market and let more people know other cryptocurrencies which increase the chance of increasing the price for other cryptocurrencies. Hence Bitcoin return could potentially affect the returns for other cryptocurrencies. Such correlation has significant implication for investors. If the correlation is positive, then investors could potentially obtain returns from including cryptocurrencies in their portfolio and bearing a lower level of risk.

In order to examine such relationship, this study mainly focuses on three main research questions. Is there a co-movement between Bitcoin and Litecoin, which could be examined in two aspects including market efficiency and causality relationship between Bitcoin and Litecoin returns? Do factors of one cryptocurrency interact with the return of another cryptocurrency? For instance, can the number of miners from one cryptocurrency market affect the return of another cryptocurrency? Finally, how volatilities are transmitted between Bitcoin and Litecoin? Investigation on volatility transmission could be examined in both conditional mean and conditional variance-covariance equations. In the latter case, a spill-over effect could be observed through the causality relationship between lags of the variance of one cryptocurrency and the current variance of another cryptocurrency. Four null hypotheses could be set for the investigation:

a) H_0: Neither Bitcoin nor Litecoin markets are efficient.
b) H_0: There does not exist causality relationship between Bitcoin and Litecoin returns.
c) H_0: There does not exist factors of one cryptocurrency affecting current returns of both Bitcoin and Litecoin.
d) H_0: There does not exist spill-over effect between Bitcoin and Litecoin markets

3.4. Methodology

3.4.1. Conditional mean models

3.4.1.1. VAR(p) & VARX(p,q)

A n-dimensional multivariate time series $\{y_t\}_{t=1}^{T}$ is said to follow a vector autoregressive model with lag order p if it follows the linear equation:

$$y_t = a + \sum_{l=1}^{p} \Phi^{(l)} y_{t-l} + v_t$$

Equation 3.4.1.1

where $y_t \in \mathbb{R}^n$, $a \in \mathbb{R}^n$ is a vector of intercepts, $\Phi^{(l)}$'s are $n \times n$ coefficient matrices, $v_t \in \mathbb{R}^n$ is a vector of errors (Sims, 1980). If m-dimensional exogenous time series $\{x_t\}_{t=1}^{T}$ with order q is added to the above equation. Then the model becomes $VARX(p,q)$ model which could be expressed mathematically as follow:

$$y_t = c + \sum_{l=1}^{p} \Phi^{(l)} y_{t-l} + \sum_{j=0}^{q} \Psi^{(j)} x_{t-j} + \varepsilon_t$$

Equation 3.4.1.2

for t=1, …, T

where $\Psi^{(j)}$'s are $m \times m$ coefficients matrices and $\varepsilon_t \in \mathbb{R}^n$ (Blachard and Quah, 1989).

3.4.2. Conditional variance model

3.4.2.1. Univariate ARCH/GARCH

The VARX model assumes the expected value for variance is constant at any time. However, it is common for financial data to exist volatility clustering where the variance varies over time. The regression will still be unbiased even with the presence of heteroskedasticity. But the estimation for standard errors and confidence interval will be too narrow to give accurate results. ARCH and GARCH models could be used to model time variant variance. Ljung-Box Q-test could be used to examine the ARCH effect via autocorrelation or White test could be used to detect whether variance is constant over time.

Let y_t be price return of assets, an ARCH(q) process could be defined as the following:

$$y_t = \mu + \varepsilon_t$$
$$\{\varepsilon_t | \phi_t\} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

Equation 3.4.2.3

where μ is the mean of series y_t, error term ε_t is a series of return residuals, ϕ_t represents the past information set, ε_t^2 is also known as ARCH term. The ARCH model allowed data to decide the optimal weights to use in forecasting the variance conditional on past information rather than fixing the number of most recent observations which assumes the variance of return is equally weighted for that fix period, ie rolling standard deviation. Hence, ARCH provides reasonable forecasting.

Based on ARCH model, another model provides better ability in forecasting variance. GARCH(p,q) model added p-lag GARCH terms into the variance equation of ARCH(q) model which is expressed as the following:

$$y_t = \mu + \varepsilon_t$$
$$\{\varepsilon_t | \phi_t\} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

Equation 3.4.2.4

Similar to rolling standard deviation technique, GARCH model also uses weighted average of past variance but with declining weight that never die away. Therefore, the new information weights more than old information which could be used to deal with clustering volatility effectively.

There exist a wide range of GARCH types models including EGARCH, GARCH-M, TGARCH which are the most popular used types of GARCH models. Exponential generalized autoregressive heteroskedastic model has the following equation:

$$log\sigma_t^2 = w + \sum_{k=1}^{q} \alpha_k g(Z_{t-k}^2) + \sum_{k=1}^{p} \alpha_k log\sigma_{t-k}^2$$

Equation 3.4.2.5

such model allows volatility to react asymmetric to negative and positive news.

The goal of volatility analysis is to explain volatility. While time series structure is good at forecasting, it does not help in explaining causes of volatility. Therefore, it might be helpful to directly include exogenous variables into the GARCH model which is called GARCH-M model. GARCH-M has the same structure as GARCH model except that there also exist heteroskedastic term in the mean equation of GARCH model. It is shown as follow:

$$y_t = \mu + \lambda\sigma_t + \varepsilon_t$$
$$\{\varepsilon_t|\phi_t\} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

Equation 3.4.2.6

3.4.3. Multivariate GARCH

It is often that volatility of one asset influence the volatility of another in financial market. It is important to examine the comovement of different asset returns. This motivate the development of multivariate GARCH (MGARCH) studies. MGARCH model should be parsimonious enough while maintaining flexible to present the dynamics of conditional variance and covariance which should be positive definite. The development of all the MGARCH focus on the following three aspects:

1. Flexibility: what MGARCH could do, what information could be achieved from estimation.
2. Parsimonious specification: the number of estimated parameters increase rapidly if the number of assets exceed two. Simplifying the model could help to interpretate the parameters easily. The downside is that most of MGARCH which satisfy this condition may not be able to capture the dynamics of relevant covariance matrix.
3. Positive definite feature for variance covariance matrix.

In the following, bivariate GARCH will be review rather than multivariate GARCH in general, as the goal of this chapter is to examine two kinds of cryptocurrencies.

$$y_t = \mu_t(\theta) + \varepsilon_t$$
$$\varepsilon_t = \mathcal{H}_t^{\frac{1}{2}}(\theta) z_t \qquad \textit{Equation 3.4.3.1}$$
$$\varepsilon_t \sim N(O, I_2)$$

where $\mu_t(\theta)$ is the conditional mean vector, z_t is a random vector with expectation and variance being zero and identity matrix of order 2. $\mathcal{H}_t^{\frac{1}{2}}(\theta)$ is 2×2 positive definite matrix such that $\mathcal{H}_t$ is the conditional variance matrix of y_t. Note that $\mathcal{H}_t^{\frac{1}{2}}$ could be obtained via Cholesky factorization of $\mathcal{H}_t$.

Different types of MGARCH models depends on different ways of defining variance covariance matrix. Silvennoinen and Terasvirta (2007) classified MGARCH models into four categories:

1. **Models of the conditional covariance matrix;** In this class the conditional covariance matrices, $\mathcal{H}_t$, are modelled directly. This class includes the VEC and BEKK models. These models were among the first parametric MGARCH models.

2. **Factor models;** The idea of factor models comes from economic theory. In this class the conditional covariance matrices are motivated by parsimony. The process $\boldsymbol{a}_t$ is assumed to be

generated by a (small) number of unobserved heteroskedastic factors, hence these models are called factor models. These factors can be studied and one may make assumptions that some characteristics of the data is captured, similar as for principal component analysis. This approach has the advantage that it reduces the dimensionality of the problem when the number of factors relative to the dimension of the return vector $\boldsymbol{a_t}$ is small.

3. **Models of conditional variances and correlations;** The models in this class are built on the idea of modelling the conditional variances and correlations instead of straightforward modelling the conditional covariance matrix.

4. **Nonparametric and semiparametric approaches;** Models in this class form an alternative to parametric estimation of the conditional covariance structure. The advantage of these models is that they do not impose a particular structure (that can be misspecified) on the data.

3.4.3.1. Models of the conditional covariance matrix

3.4.3.1.1. VEC and Diagonal VEC

Bollerslev et al. (1988) used univariate GARCH to generalize multivariate GARCH. Every conditional variance and covariance depends on lag of conditional variance and covariance, lag of squared errors and cross product of error terms. It is expressed as the following:

$$VECH(\mathcal{H}_t) = C + AVECH(E_{t-1}E_{t-1}^T) + BVECH(\mathcal{H}_{t-1})$$

$$\mathrm{E}_t|\psi_{t-1} \sim N(0, \mathcal{H}_t)$$

Equation 3.4.3.1.1.1

where $\mathcal{H}_t$ is a 2 × 2 conditional variance-covariance matrix, E_t is a 2 × 1 innovation (disturbance) vector, ψ_{t-1} represents the information set at time t −1, *C* is a 3×1 parameter vector, *A* and *B* are 3×3 parameter matrices and *VECH*(·) denotes the column-stacking operator applied to the upper portion of the symmetric matrix.

If $\mathcal{H}_t = \begin{pmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{pmatrix}$ and $E_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$,

then $\mathrm{VECH}(\mathcal{H}_t) = \begin{pmatrix} h_{11t} \\ h_{12t} \\ h_{22t} \end{pmatrix}$ and $\mathrm{VECH}(E_t) = \begin{pmatrix} \varepsilon_{1t}^2 \\ \varepsilon_{2t}^2 \\ \varepsilon_{1t}\varepsilon_{2t} \end{pmatrix}$.

Therefore, it is clear that the conditional variances and conditional covariance depend on the lag values of all of the conditional variances of and conditional covariance between asset returns in the series, as well as the lag squared errors and the error cross products. Estimation of such a model would induce large amount of parameters, even in the two-asset case considered here. Therefore, the *VECH* model's conditional variance covariance matrix has been restricted such that *A* and *B* are assumed to be diagonal. This reduces the number of parameters to be estimated and the model, known as a diagonal *VECH*, which could be expressed as the following:

$$h_{ij,t} = w_{ij} + \alpha_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta_{ij}h_{ij,t-1}$$ *Equation 3.4.3.1.1.2*

where w_{ij}, α_{ij} and β_{ij}.

3.4.3.1.2. BEKK

The disadvantage of VEC and Diagonal VEC models is that covariance matrices are not guaranteed to be positive definite. Engle and Kroner (1995) developed BEKK model that corrects the problem by ensuring positive definite for covariance matrix.

$$\mathcal{H}_t = W^T W + A^T \mathcal{H}_{t-1} A + B^T E_{t-1} E_{t-1}^T B$$ *Equation 3.4.3.1.2.1*

where *A* and *B* are 3 × 3 matrices of parameters and *W* is an upper triangular 3 × 3 matrix. The positive definiteness of the covariance matrix is ensured due to the quadratic nature of the terms on the equation's right-hand side. A^T denotes the transpose of matrix A, E_{t-1}^T denotes the transpose of matrix E_{t-1}.

As discussed earlier, the focus of MGARCH model is to provide flexible, parsimonious specification while ensuring positive definiteness of covariance matrix. However, there is a dilemma between flexibility and parsimony. BEKK models are flexible but require too many parameters for multiple time series of more than four elements. Diagonal VEC and BEKK models are much more parsimonious but very restrictive for the cross-dynamics. They might not be suitable if volatility transmission is the object of interest. But they are usually good at presenting dynamics of variance and covariance.

3.4.3.1.3. Factor model

Engle, Ng and Rothschild (1990) proposed the first factor GARCH (F-GARCH) model which reduces help to reduce the number of estimated parameters by using a small number of factors, K<N. If observed series, r_t is explained by factors f_t and B is a $N \times K$ matrix which is expressed as the following:

$$r_t = Bf_t + \varepsilon_t \qquad \text{Equation 3.4.3.1.3.1}$$

Assume that Ω and Γ are $N \times N$ and $K \times 1$ conditional covariance matrix for error terms ε_t and factor f_t respectively. If ε_t and f_t are uncorrelated.

The conditional covariance matrix for r_t could be expressed as the following:

$$\mathcal{H}_t = \Omega + \sum_{k=1}^{K} w_k w_k^T f_{k,t} \qquad \text{Equation 3.4.3.1.3.2}$$

where Ω is a positive semi-definite matrix, w is a $N \times 1$ vector for factor weight, $f_{k,t}$ represents factor which has the following GARCH-type structure:

$$f_{k,t} = w_k + a_k(\varpi_k^T r_{t-1})^2 + b_k f_{k,t-1} \qquad \text{Equation 3.4.3.1.3.3}$$

where w_k, a_k and b_k are scalers and ϖ_k is a $N \times 1$ weight vector.

3.4.3.1.4. Orthogonal model

Alexander (2001) proposed orthogonal GARCH (O-GARCH) with assumption that a linear transformation of uncorrelated components could be used to obtain observed data. The linear transformation matrix is an orthogonal matrix. This model avoids estimating off-diagonal elements for parameter matrices in multivariate GARCH because the model does not estimate the original dataset. The O-GARCH model could expressed as follow:

$$u_t = V_K f_t \qquad \text{Equation 3.4.3.1.4.1}$$
$$V_K = P_K \Lambda_K^{1/2}$$

where $u_t = D^{1/2}\varepsilon_t$ represents standardized residuals. The K factors are used to generate dataset via orthogonal transformation. The transformation matrix is given by eigenvectors $\bar{R}$. $\Lambda_k$is a $K \times K$ diagonal matrix of eigenvalues of $\bar{R}$ and P_K is the related orthogonal matrix of eigenvectors.

The factors vector has the following conditional mean and variance characteristics:

$$E_{t-1}[f_t] = 0$$

$$V_{t-1}[f_t] = Q_t = diag(\sigma^2_{f1,t}, \dots, \sigma^2_{fk,t})$$

$$\sigma^2_{f_i,t} = \left(1 - \sum\nolimits_{h=1}^{p} \alpha_{ih} - \sum\nolimits_{h=1}^{q} \beta_{ih}\right) + \sum\nolimits_{h=1}^{p} \alpha_{ih}\, f^2_{i,t-h} + \sum\nolimits_{h=1}^{p} \beta_{ih}\, \sigma^2_{f_i,t-h}$$

Equation 3.4.3.1.4.2

The conditional covariance matrix for error terms ε_t=$D^{1/2}R_tD^{1/2}$, where $R_t = V_mQ_tV_m^T$.

3.4.3.2. Models of conditional variances and correlations

3.4.3.2.1. Constant conditional correlation (CCC)

Bollerslev (1990) proposed the first conditional correlation model which focus on correlation of assets rather than covariance of assets. The conditional variance is estimated indirectly via conditional correlation. Assume $\sigma_{ij,t}$ is the covariance between asset i and j and $\sigma^2_{i,t}$ is the conditional variance from univariate GARCH. The assumption that constant correlation between two assets could be denoted as ρ_{ij} which has the following formula:

$$\rho_{ij} = \frac{\sigma_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$$

Equation 3.4.3.2.1.1

⇨ $\sigma_{ij,t} = \rho_{ij}\sigma_{i,t}\sigma_{j,t}$

A 2×2 correlation matrix could be expressed as follows:

$$P = \begin{pmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{pmatrix}$$

In terms of matrices, the temporal variation only depends on conditional variance as the

$$\mathcal{H}_t = D_t^{1/2} P D_t^{1/2}$$ *Equation 3.4.3.2.1.2*

where D_t represents the diagonal matrix of conditional variances and P represents the conditional correlation matrix of innovation terms from the univariate GARCH. They are both positive definite suggesting variance-covariance matrix is also positive definite. However, such model is too restricted and studies show it is not plausible to assume constant correlation for most of the financial data. Both Engle and Sheppard (2001) and Tse and Tsui (2002) developed time-varying conditional correlations which are called dynamic correlation model and time-varying correlation model respectively. They have different concept and will be introduced separately.

3.4.3.2.2. Dynamic conditional correlation (DCC)

Engle and Sheppard (2001) introduced the dynamic conditional correlation model where covariance matrix is decomposed into conditional standard deviations, D_t, and time-variant correlation matrix, P_t. As the conditional correlation becomes time-variant, the above expression changes to the following:

$$\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$$ *Equation 3.4.3.2.2.1*

which has the following matrix form:

$$P_t = Diag(Q_t)^{-1/2} \times Q_t \times Diag(Q_t)^{-1/2}$$
$$Q_t = (1 - \zeta_1 - \zeta_2)\bar{Q} + \zeta_1(u_{t-1}u_{t-1}^T) + \zeta_2 Q_{t-1}$$ *Equation 3.4.3.2.2.2*

where $\bar{Q}$ represents the unconditional covariance matrix of standardized residuals from univariate GARCH, $u_t = \{\varepsilon_{i,t}/\sigma_{i,t}\}_{i=1,\dots,n}$ and $Diag(Q_t)^{-1/2}$ represents the diagonal elements of diagonal matrix Q_t. Conditional correlation matrix P_t would be positive definite from estimation if $0 < \zeta_1, \zeta_2 < 1$ and $\zeta_1 + \zeta_2 < 1$.

3.4.3.2.3. Asymmetric dynamic conditional correlation (AG-DCC)

Cappiello, Engle and Sheppard (2006) proposed an extension of DCC model that allow for asymmetric dynamics for volatility and correlation matrix. As in DCC model, after univariate volatility model being estimated, the residuals are being standardized and used to estimate correlation parameters. AG-DCC could be specified as the following:

$$P_t = Diag(Q_t)^{-1/2} \times Q_t \times Diag(Q_t)^{-1/2}$$
$$Q_t = (\bar{Q} - A^T\bar{Q}A - B^T\bar{Q}B - G^T\bar{N}G) + A^T(u_{t-1}u_{t-1}^T)A + G^T(n_{t-1}n_{t-1}^T)G + B^TQ_{t-1}B$$

Equation 3.4.3.2.3.1

where A, B and G are $k \times k$ matrices, $n_t = I[u_t < 0] \odot \varepsilon_t$ is an $k \times 1$ indicator function that takes the value of 1 if the standardized residual is negative, otherwise equal to zero and $\odot$ represents a Hadamard product. $\bar{N} = E[n_t n_t^T]$ and $\bar{Q} = E[u_t u_t^T]$ are estimated by sample analogues. The conditional covariance matrix $\mathcal{H}_t = D_t^{1/2} P D_t^{1/2}$ is positive definite if $(\bar{Q} - A^T\bar{Q}A - B^T\bar{Q}B - G^T\bar{N}G)$ is positive definite.

3.4.3.2.4. Time-varying conditional correlation (TVC)

Tse and Tsui (2002) construct conditional correlation matrix, P_t, in autoregressive moving average (ARMA) type:

$$P_t = (1 - \varrho_1 - \varrho_2)P + \varrho_1 P_{t-1} + \varrho_2 \Psi_{t-1}$$

Equation 3.4.3.2.4.1

where P={ρ_{ij}} is a time-invariant correlation matrix and $\Psi_t = \{\psi_{ij,t}\}$ represents a set of past standardised residuals which is a sample correlation matrix of standardized residuals:

$$\psi_{ij,t} = \frac{\sum_{h=0}^{m-1} u_{i,t-h}\, u_{j,t-h}}{\sqrt{(\sum_{h=0}^{m-1} u_{i,t-h}^2)(\sum_{h=0}^{m-1} u_{j,t-h}^2)}}$$

Equation 3.4.3.2.4.2

for $1 \leq i \leq j \leq n$

where $u_t = D_t^{-1}\varepsilon_t$. Let $B_t = (\sum_{h=0}^{m-1} u_{i,t-h}^2)^{1/2}$ be $n \times n$ diagonal matrix. The above equation could be expressed as:

$$\Psi_{t-1} = B_{t-1}^{-1} E_{t-1} E_{t-1}^T B_{t-1}^{-1}$$

Equation 3.4.3.2.4.3

If $m \geq n$, then Ψ_{t-1} is positive definite. If $0 \leq \varrho_1, \varrho_2 \leq 1$ and $\varrho_1 + \varrho_2 \leq 1$, then P_t is positive definite.

3.4.4. Estimation

3.4.4.1. Quasi maximum likelihood method

Let F_t be the information available at time t, $H_t(\theta)$ be a positive condition covariance $N \times N$ matrix with $N \times 1$ residual vector ε_t which is parameterized by vector θ.

Engle and Sheppard (2001) proposed a 2-steps approach for estimating parameters of DCC-GARCH model. Let $\Phi = (\theta', \phi', \psi')$ represents the set of parameters to estimate for DCC-GARCH where θ and ϕ represents the parameters for mean and variance and ψ represents the correlation parameters and they are asymptotically normal. The first step is to estimate mean and variance parameters θ and ϕ which are estimated by maximizing the Gaussian log-likelihood function.

$$\log L_1(\theta, \phi) = -\frac{N \cdot T}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} log|D_t| - \frac{1}{2} \sum_{t=1}^{T} \varepsilon_t' \, \varepsilon_t$$

Equation 3.4.4.1.1

The second step used the estimated mean and variance parameters to estimate correlation parameters by maximizing the following function:

$$\log L_2(\psi|\theta, \phi) = -\frac{1}{2} \sum_{t=1}^{T} log|R_t| - \frac{1}{2} \sum_{t=1}^{T} \hat{\varepsilon}_t' \, R_t^{-1} \hat{\varepsilon}_t$$

Equation 3.4.4.1.2

where $\hat{\varepsilon}$ represents the standardized residuals that was obtained in the first step.

3.4.5. Diagnostic tests

Diagnostic tests should be carried out to check the adequacy of a multivariate GARCH model. If the model is appropriate, then standardized errors should be identically independently distributed. There are mainly three types of diagnostic tests for multivariate GARCH model. First test examine the autocorrelation of the model called Portmanteau test. Second test is residual-based diagnostics. The final test checks the goodness of errors for each series and goodness of the multivariate fit.

3.4.5.1. Portmanteau statistics

Baillie and Bollerslev (1990) extended the Ljung-Box portmanteau test to multivariate form for examining the serial correlation. It has the following test function:

$$H(p) = T^2 \sum_{i=1}^{p} (\frac{1}{T-i}) tr(\widehat{C_\iota}\widehat{C_0^{-1}}\widehat{C_\iota}\widehat{C_0^{-1}})$$

Equation 3.4.5.1.1

where $\widehat{C_\iota} = \frac{1}{T}\sum_{t=i+1}^{T}(x_t - \bar{x})(x_{t-i} - \bar{x})'$ is the sample autocovariance matrix of order I of x_t and $H(p) \sim \chi^2(n^2 p)$ with null hypothesis that there is no ARCH effects. This test is to detect the misspecification of conditional variance matrix.

3.4.5.2. Residual-based tests

These tests run regression of cross-products of standardized residuals on explanatory variables and check the statistical significant of coefficient. Since the errors are standardized, the usual OLS would not work. Tse (2002) establish asymptotic distribution of OLS estimator.

Let $\hat{u}_{it} = \widehat{\varepsilon_{\iota t}} \Big/ \sqrt{\widehat{h_{\iota\iota t}}}$ as the ith (i=1,..N) standardized residual at time t,

$\hat{\rho}_{ijt} = \widehat{h_{\iota j t}} \Big/ \sqrt{\widehat{h_{\iota\iota t}}\widehat{h_{jjt}}}$ as the estimated conditional correlation.

Tse (2002) propose the following regressions:

$$\hat{u}_{it} - 1 = \widehat{d'_{\iota t}}\delta_i + \xi_{it} \qquad i = 1, \dots, N$$

Equation 3.4.5.2.1

$$\hat{u}_{it}\hat{u}_{jt} - \widehat{\rho_{\iota j t}} = \widehat{d'_{\iota j t}}\delta_{ij} + \xi_{ijt} \qquad 1 \le i \le j \le N$$

where $\widehat{d'_{\iota t}}$ and $\widehat{d'_{\iota\iota t}}$ are estimated counterpars of respectively $d_{it} = (u_{i,t-1}^2, \dots u_{i,t-p}^2)$, $d_{ijt} = (u_{i,t-1}u_{j,t-1}, \dots, u_{i,t-p}u_{j,t-p})$ and δ_i and δ_{ij} are regression coefficients.

3.5. Model for estimation

The objective of this chapter is to examine the dynamic relationship between Bitcoin and Litecoin returns. For this purpose, a bivariate VARX-GARCH-MEAN model will be employed using the BEKK conditional variance and covariance specification and the DCC specification will also be included for robustness purposes. Volatilities of both Bitcoin and Litecoin lag returns will be considered in the conditional mean equations along with some exogenous variables. Therefore, VARX-GARCH-Mean model will be used for estimating conditional mean equations in order to capture the influence of past volatilities and cross volatilities as well as the effect from exogenous variables. This chapter mainly interpret results from BEKK model and use DCC model for robustness check. Both BEKK and DCC models are commonly used methodology due to their advantages. The BEKK model allows to examine whether there exist cross effects of lags of volatilities and squared residuals on current volatilities for both Bitcoin and Litecoin. However, BEKK only captures the time-varying properties of conditional covariance rather than dynamic conditional correlation which takes into account of past return shocks on volatility and correlation. The DCC model considers correlation in addition to variance-covariance of Bitcoin and Litecoin returns, which is an important factor when analysing risk and asset allocation for Bitcoin and Litecoin. Both BEKK and DCC ensure positive-definite of covariance matrix. After estimating unrestricted the BEKK and DCC models, any insignificant factors will be removed from the models so that two restricted models will be estimated and compared to the unrestricted models. In the following, I present the unrestricted BEKK and DCC models, which have the same conditional mean equations but differ in the conditional variance equations. For notational convenience, we define the following variables: $r_{b,t}$ ($r_{l,t}$) represents difference of logs of Bitcoin (Litecoin) price between period t and t-1; $w_{b,t-1}$ ($w_{l,t-1}$) represents number of Wikipedia views for Bitcoin (Litecoin) at time t which is measured for every 1000 views; $t_{b,t-1}$ ($t_{l,t-1}$) represents transaction volume for Bitcoin (Litecoin) at time t which is measured for every million US dollars; $dh_{b,t-1}$ ($dh_{l,t-1}$) represents difference of log of hashrate for Bitcoin (Litecoin) at time t. The reason for only differencing the hashrate variable is the results from the unit root tests presented below.

3.5.1. BEKK

Conditional mean equations:

$$\begin{aligned} r_{b,t} = c_1 &+ \varphi_{11} lr_{b,t-1} + \varphi_{12} lr_{b,t-2} + \tau_{11} lr_{l,t-1} + \tau_{12} lr_{l,t-2} \\ &+ \phi_{11} w_{b,t-1} + \phi_{12} w_{l,t-1} + \gamma_{11} lv_{b,t-1} + \gamma_{12} lv_{l,t-1} \\ &+ \delta_{11} dh_{b,t-1} + \delta_{12} dh_{l,t-1} + \lambda_{11} \sigma^2_{b,t-1} \\ &+ \lambda_{12} \sigma_{bl,t-1} + \lambda_{13} \sigma^2_{l,t-1} + \varepsilon_{b,t} \end{aligned}$$ *Equation 3.5.1.1*

$$\begin{aligned} r_{l,t} = c_2 &+ \tau_{21} lr_{b,t-1} + \tau_{22} lr_{b,t-2} + \varphi_{21} lr_{l,t-1} + \varphi_{22} lr_{l,t-2} \\ &+ \phi_{21} w_{b,t-1} + \phi_{22} w_{l,t-1} + \gamma_{21} lv_{b,t-1} + \gamma_{22} lv_{l,t-1} \\ &+ \delta_{21} dh_{b,t-1} + \delta_{22} dh_{l,t-1} + \lambda_{21} \sigma^2_{b,t-1} \\ &+ \lambda_{22} \sigma_{bl,t-1} + \lambda_{23} \sigma^2_{l,t-1} + +\varepsilon_{l,t} \end{aligned}$$ *Equation 3.5.1.2*

Conditional variance equation for BEKK:

$$H_t = WW' + AE_{t-1}E'_{t-1}A' + BH_{t-1}B'$$ *Equation 3.5.1.3*

where W is a lower triangular 2×2 matrix, both A and B are 2×2 matrices of parameters for lag of variance covariance matrix and product of lag of errors matrices. Lag length for BEKK(1,1) is chosen based on ARCH effect test on residuals. The elements of these matrices could be shown as follow:

$$H_t = \begin{bmatrix} \sigma_{b,t} & \sigma_{bl,t} \\ \sigma_{lb,t} & \sigma_{l,t} \end{bmatrix}; E_t E'_t = \begin{bmatrix} \varepsilon^2{}_{b,t} & \varepsilon_{b,t}\varepsilon_{L,t} \\ \varepsilon_{l,t}\varepsilon_{b,t} & \varepsilon^2{}_{b,t} \end{bmatrix}$$

$$W = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}; A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}; \; B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix};$$

3.5.2. DCC

For the purpose of robustness check, this section shows the estimated DCC model which allows the covariance to change from one period to the next period.

Engle (1999) developed DCC model where the conditional mean equations are the same as in BEKK model but the conditional variance covariance and correlation model are specified as follow. Given that the conditional variance covariance matrix is specified as:

$$H_t = D_t P_t D_t \qquad \textit{Equation 3.5.2.4}$$

where $D_t = \{diag\sqrt{\sigma_{i,t-1}}\}$ is the diagonal matrix of conditional variance, $P_t = \{p_{ij,t}\}$ is the time varying correlation matrix.

The conditional variance of error terms, $\sigma^2_{b,t}$ and $\sigma^2_{l,t}$ could be obtained from the first stage of estimation process, where the univariate GARCH process is defined as follow:

$$\sigma_{b,t-1} = c_1 + a_1 \varepsilon^2{}_{b,t-1} + b_1 \sigma^2{}_{b,t-1} \qquad \textit{Equation 3.5.2.5}$$

$$\sigma_{l,t-1} = c_2 + a_2 \varepsilon^2{}_{l,t-1} + b_2 \sigma^2{}_{l,t-1} \qquad \textit{Equation 3.5.2.6}$$

In the second stage, the estimated correlation matrix is developed as follow:

$$P_t = diag(Q_t)^{-\frac{1}{2}} * Q_t * diag(Q_t)^{-\frac{1}{2}} \qquad \textit{Equation 3.5.2.7}$$

where Q_t is the variance covariance matrix of standardized residuals ($z_t = \frac{\epsilon_t}{\sigma_t}$), which takes the following form:

$$Q_t = (1 - w_1 - w_2)\bar{Q} + \ w_1 z_{t-1} z'_{t-1} + w_2 Q_{t-1} \qquad \textit{Equation 3.5.2.8}$$

where $\bar{Q} = \frac{1}{T}\sum_{t=1}^{T} z_t z'_t$, $w_1 + w_2 < 1$, $w_1, w_2 > 0$, parameters w_1, w_2 capture the effects of past shocks and past dynamic conditional correlations on current dynamic conditional correlation.

Given that only Bitcoin and Litecoin are being examined, the correlation estimator of $P_t = diag(Q_t)^{-\frac{1}{2}} * Q_t * diag(Q_t)^{-\frac{1}{2}}$, the correlation estimator could be expressed as the following form:

$$p_{bl,t} = \frac{q_{bl,t}}{\sqrt{q_{bb,t}q_{ll,t}}} = \frac{(1-w_1-w_2)\overline{q_{bl}} + w_1 z_{t-1}z'_{t-1} + w_2 q_{bl,t-1}}{\sqrt{\{(1-w_1-w_2)\overline{q_{bb}} + w_1 z_{t-1}z'_{t-1} + w_2 q_{bb,t-1}\}\{(1-w_1-w_2)\overline{q_{ll}} + w_1 z_{t-1}z'_{t}}}$$

Equation 3.5.2.9

where $q_{bl,t}$ indicates the covariance of Bitcoin and Litecoin returns at time t, $q_{bb,t}$ and $q_{ll,t}$ represent the variance of Bitcoin and Litecoin returns at time t respectively.

3.6. Data

Original daily data for both Bitcoin and Litecoin was collected for the period between 17/07/2013 and 20/01/2016. Four kinds of data were collected for both Bitcoin and Litecoin including prices, transaction volumes, hashrate and Wikipedia views. Both Bitcoin[3] and Litecoin[4] prices and transaction volume were collected from dc-chart.com which stores all the historical values of Bitcoin and Litecoin prices and transaction volume from BTC-e exchange market in US dollar. Wikipedia views for Bitcoin[5] and Litecoin[6] were collected by Wikipedia search engine called article traffic statistics which tracks the number of searches of related cryptocurrencies. Such search does not only link to some prominent public article but also show other artistic work and related news on cryptocurrencies.

Hashrate for Bitcoin[7] and Litecoin[8] were collected from bitinfocharts.com which shows cryptocurrencies statistics for varies types of data of cryptocurrencies. Some cryptocurrency data are predetermined or adjusted to be unchanged over a period of time. However, two of the technical data including “difficulty” and “hashrate” are affected by number of miners and change in mining technology as discussed in section 1.4.5.3. These two factors relate to each other in order to maintain the block time which is the time taken for a block to be solved.

[3] Bitcoin closing price and transaction volume: https://dc-charts.com/raw_btc.php?ex=1&cu=0&tz=6&ar=1

[4] Litecoin closing price and transaction volume: https://dc-charts.com/raw_ltc.php?ex=0&cu=1&tz=6&ar=1

[5] Bitcoin Wikipedia view: http://stats.grok.se/en/200901/Bitcoin

[6] Litecoin Wikipedia view: http://stats.grok.se/en/201403/Litecoin

[7] Bitcoin hashrate: https://bitinfocharts.com/comparison/hashrate-btc-ltc.html

[8] Litecoin hashrate: https://bitinfocharts.com/comparison/hashrate-ltc.html

Difficulty is adjusted by the system according to the change of hashrate that is provided in the whole network so that an increase in total hash-rate will not increase the speed of creating a new block. Therefore, hashrate is the only unpredictable technical factor which could be used to represent the number of miners in the network. The change in the number of miners might have an effect on cryptocurrency returns because miners provide decentralization feature of cryptocurrency and strengthen the network. A hash is the output of a hash function while hashrate represents the speed at which a computer is completing an operation in the cryptocurrency code. A higher hashrate increases the chance of finding the next block and receive reward for a miner.

Transaction volume represents the US dollar value of cryptocurrencies being traded during the time period. There were some missing values in the dataset including prices, transaction volumes and Wikipedia views. There were three sets of missing values for Bitcoin prices and Bitcoin transaction volumes on 11/02/2014, 12/08/2014 and 12/07/2015. Two sets of missing values for Litecoin prices and transaction volumes on 16/03/2014 and 17/03/2014. Two sets of missing values for Bitcoin and Litecoin Wikipedia views which are on 06/01/2014 and 28/08/2014. These values were extrapolated by taking the average of the previous and the next observation. A data point on 26/01/2014 for Litecoin transaction volume was changed into average of the previous two values because that data point did not seem to be reasonable. On 26/01/2014 the transaction volume for Litecoin was less than 2 Litecoins which was significantly lower than average values of that week. The transaction volumes were more than 20,000 Litecoins each day during that week. These missing values should not have big impact for data analysis because there are 918 observations for each time series.

3.6.1. Data description

3.6.1.1. Data transformation

Differences of the logs of prices for both Bitcoin and Litecoin were used to obtain logarithm returns of Bitcoin and Litecoin respectively. Diagram 1 shows the raw data of each time series. Before testing unit root of these series, both transaction volumes and hashrate were transformed. The transaction volume was first transformed so that they are in terms of US dollar rather than the number of cryptocurrencies being traded by multiplying the prices of cryptocurrencies. Then the unit for transaction volumes were changed into every million US dollar by dividing 1 million. From now on, the transaction volume refers to the amount of cryptocurrencies being traded in millions of US dollar. The units for hashrates for both Bitcoin and Litecoin were changed into GH/s which means 1 million hash per second. Unit of wikipedia views are presented by every one million views.

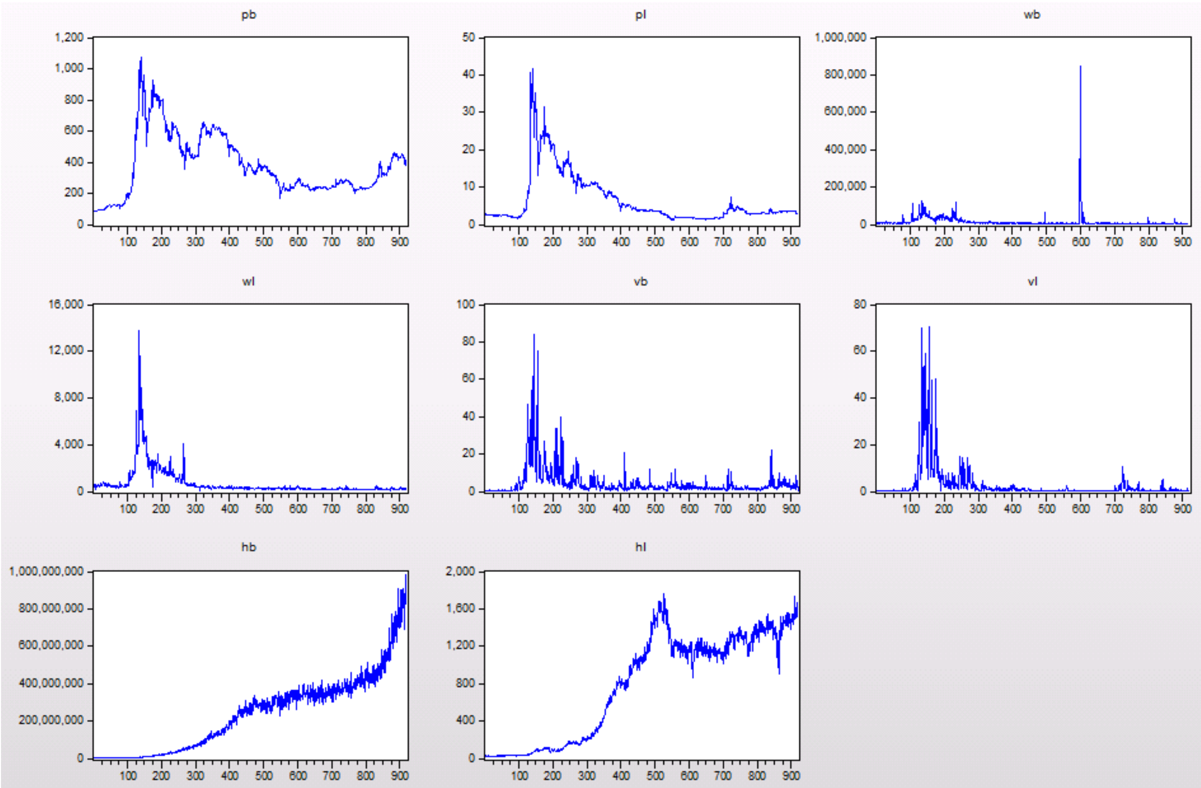


Diagram 1: Time series plots for all series. Transaction volume and hashrates series have been modified as described below. Bitcoin and Litecoin price, transaction volume, Wikipedia views and hashrate are represented by pb, pl, vb, vl, wb, wl, hb and hl respectively. Where letters p, v, w, h indicates daily closing price, transaction volume, Wikipedia views and hashrate. While letters b and l represent Bitcoin and Litecoin.

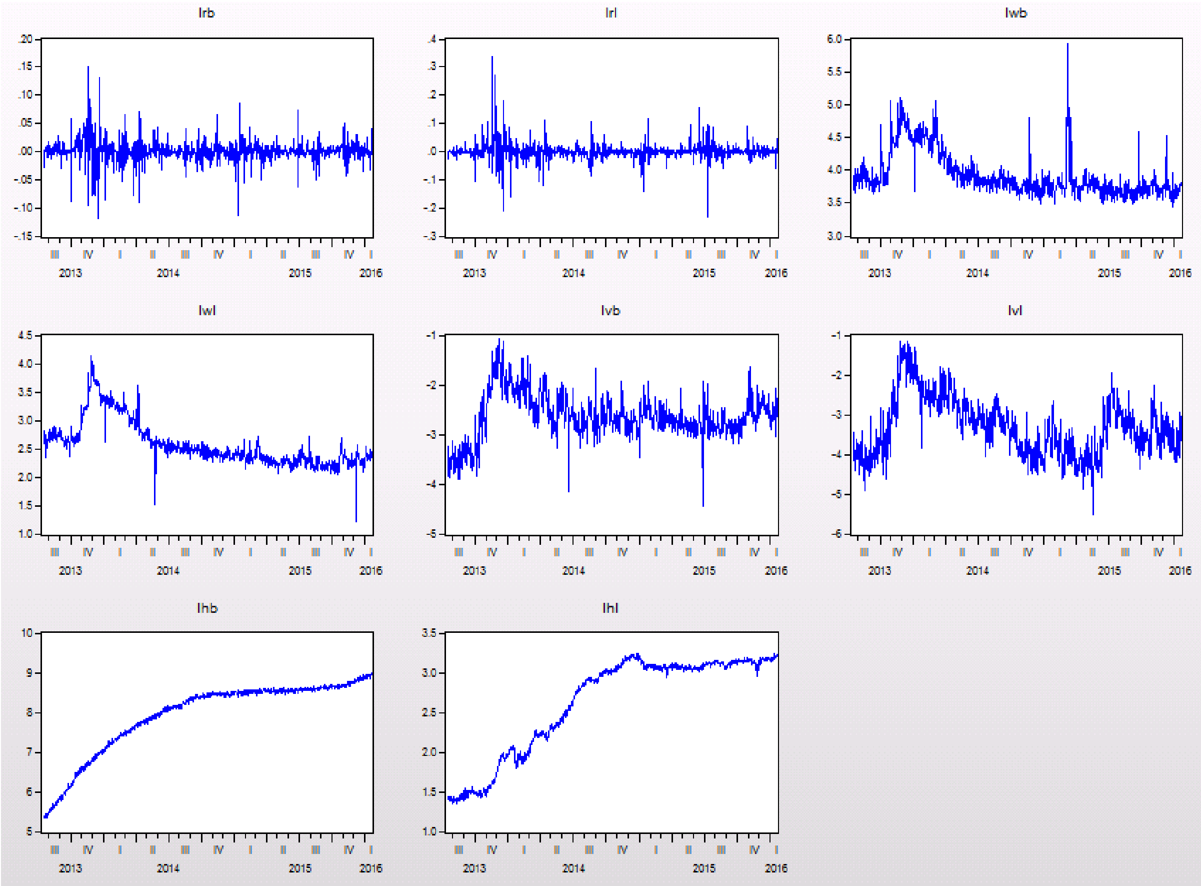


Diagram 2: Log of Bitcoin and Litecoin returns are represented by lrb and lrl respectively. Log transformation for transaction volumes, Wikipedia views and Hashrates for Bitcoin and Litecoin are represented by lvb, lvl, lwb, lwl, lhb and lhl where the first letter l is included to indicate the log transformation.

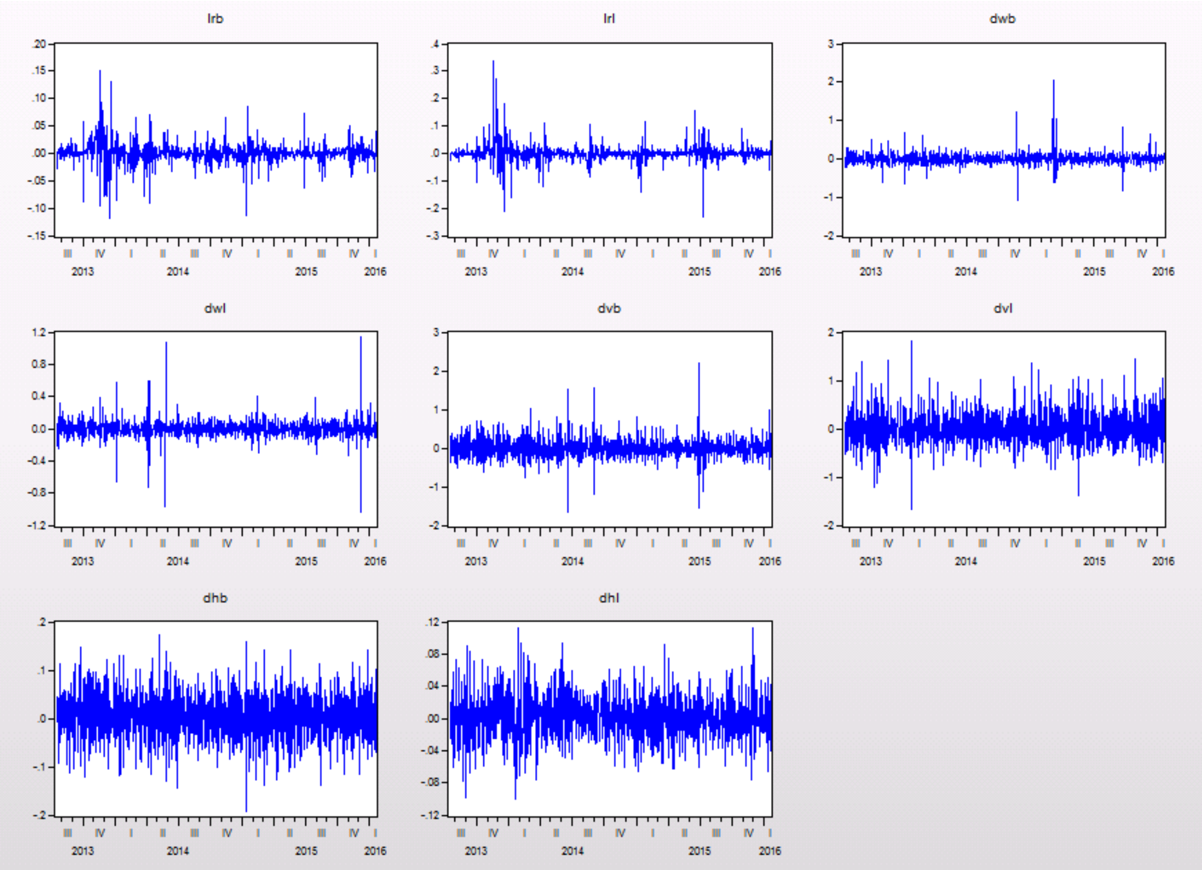


Diagram 3: First differenced of log transformed series.

3.6.1.2. Unit root tests

If the examined time series are not stationary, then estimated results could be spurious. Therefore, it is important to examine whether all examined time series do not have unit root. The following shows the type of unit root test that I will be using for testing unit root in each of the series. At first, all raw data will be tested. Then, for series which reject the unit root test will remain in their original form in order to avoid loss of information if data is being transformed further into another form. Given that there are Bitcoin and Litecoin variables for each of the four different exogenous factors. If only one cryptocurrency variable for a specific exogenous factor reject the null hypothesis but another cryptocurrency variable for that exogenous factor does not reject the null hypothesis of unit root test. Then both of these variables will be continue to test for stationarity in another form in order to be consistent for interpretation of the results. The graphs for Bitcoin and Litecoin hashrates show clear trend which imply they need to be differenced in order to get rid of the unit roots.

Augmented Dickey Fuller (ADF) test has been used to examine the stationarity of the series before any transformation of data. The test procedure for ADF test applies to the following model:

$$\triangle r_t = \alpha + \beta t + \gamma r_{t-1} + \delta_1 \triangle r_{t-1} + \cdots + \delta_p \triangle r_{t-p} + \varepsilon_t$$

Equation 3.6.1.2.1

where α is a constant, β, γ and δ_p are coefficients for time trend, lag of return and difference of lag of returns respectively. If $\alpha = \beta = 0$, then the model correspond to a random walk process. The unit root test has null hypothesis of $\gamma = 0$ against alternative hypothesis that $\gamma < 0$, which has the following test statistic:

$$\frac{\hat{\gamma}}{SE(\hat{\gamma})} \sim D.F.$$

Critical values are selected for Dikcy-Fuller t-distribution (1979). If the test statistic is less than critical value, then null hypothesis is rejected so that no unit root is present.

Table 1 shows unit root test results for raw data with consideration of two types of model. First type of model does not consider time trend, therefore $\beta = 0$ is taken into account. The second type of model includes time trend to see whether time trend is essential. As table 1 shows, three series are stationary at conventional level at level, which does not need to be transformed in order to remove unit root of these series which are Wikipedia views series for both Bitcoin (wb) and Litecoin (wl) and transaction volume for Bitcoin (vb). The following table shows the p-value of ADF unit root test for data after log transformation. In addition, both intercept and trend were considered.

	Intercept	Intercept and Trend (I&T)	Intercept (1st differenced)	I&T (1st differenced)
Pb	0.174	0.303	0.000***	0.000***
Pl	0.124	0.132	0.000***	0.000***
Wb	0.000***	0.000***	0.000***	0.000***
Wl	0.046**	0.048**	0.000***	0.000***
Vb	0.019**	0.040**	0.000***	0.000***
Vl	0.133	0.222	0.000***	0.000***

Hb	1.000	1.000	0.000***	0.000***
Hl	0.862	0.790	0.000***	0.000***

Table 1: Unit root test before data transformation showing p-values

Table 2 shows all series are stationary at level when considering intercept in tested equation except for Wikipedia view and hashrate series for Litecoin. However, in order to keep as much information from the series as possible, Wikipedia view series will not be transformed for estimated model. For data analysis, the following series will be used including log return for Bitcoin(lrb)/Litecoin(lrl), Wikipedia view for Bitcoin(wb)/Litecoin(wl), log of transaction volume for Bitcoin(lvb)/Litecoin(lvl) and log differenced of hashrate for Bitcoin(dhb)/Litecoin(dhl).

Intercept and trend	Intercept	Intercept and Trend (I&T)	Intercept (1^{ST} differenced)	I&T (first differenced)
lrb	0.0000***	0.0000***	0.0000***	0.0000***
lrl	0.0000***	0.0000***	0.0000***	0.0000***
lvb	0.003***	0.016**	0.0000***	0.0000***
lvl	0.077*	0.135	0.0000***	0.0000***
lwb	0.035**	0.010***	0.0000***	0.0000***
lwl	0.596	0.446	0.0000***	0.0000***
lhb	0.000***	0.000***	0.0000***	0.0000***
lhl	0.174	0.980	0.0000***	0.0000***

Table 2: unit root test for log transformation of series in level and first difference with consideration of intercept in the test equation

	lr_b	lr_l	w_b	w_l	lv_b	lv_l	dh_b	dh_l
Mean	0.000735	8.23E-05	14.37766	0.684569	-2.632625	-3.313523	0.003897	0.001904
Median	0.000464	-0.001008	6.619000	0.289000	-2.670523	-3.378985	0.005264	0.002008
Maximum	0.150374	0.338295	847.6140	13.81300	-1.076792	-1.151265	0.172603	0.112100
Minimum	-0.118303	-0.233252	2.783000	0.016000	-4.430424	-5.513733	-0.193655	-0.100969
Std. Dev.	0.020560	0.033248	39.54907	1.160582	0.466827	0.752415	0.051683	0.030095
Skewness	-0.058908	1.544099	16.31368	4.728250	0.130290	0.502247	-0.059152	0.113625

Kurtosis	13.66748	28.43564	317.4737	34.70474	3.876379	2.819274	3.148743	3.480221
Jarque-Bera	4348.452	25084.10	3819239.	41823.46	31.93995	39.80050	1.380106	10.78448
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.501550	0.004552

3.6.1.3. Summary statistics

Table 3: Descriptive statistics

Table 3 shows a summary of descriptive statistics for all series that will be used for estimating model. The mean for returns and hashrate series are close to zero. The mean of WB is larger than WL, where 14.37766 and 0.684569 indicate the mean of Bitcoin and Litecoin Wikipedia views are 14377 and 685 respectively because the unit of Wikipedia views are measured for every 1000 views. Log of transaction volume for Bitcoin and Litecoin series have negative mean since a unit of transaction volume was transformed before log transformation.

Results for Jarque-Bera suggest DHB is normally distributed at conventional level but lack of evidence to support other variables are normally distributed. Skewness of these variables indicate most of these variables have skewness values far away from the mean values which also gives evidence that they are not normally distributed.

3.6.1.4. Covariance and correlations

Covariance Analysis: Ordinary
Sample: 7/18/2013 1/20/2016
Included observations: 917
Balanced sample (listwise missing value deletion)

Covariance Correlation	lrb	lrl	wb	wl	lvb	lvl	dhb	dhl
lrb	0.000422 1.000000							
lrl	0.000376 0.550258	0.001104 1.000000						
wb	0.005719 0.007042	0.023090 0.017579	1562.424 1.000000					
wl	0.000361 0.015154	0.003279 0.085073	14.63973 0.319297	1.345481 1.000000				
lvb	0.000263 0.027433	0.000583 0.037610	3.435000 0.186255	0.298658 0.551845	0.217690 1.000000			
lvl	0.000193 0.012492	0.001661 0.066450	4.930486 0.165871	0.537908 0.616665	0.243340 0.693545	0.565510 1.000000		
dhb	-6.91E-05 -0.065067	-0.000131 -0.076530	0.007487 0.003667	0.002065 0.034459	0.000299 0.012401	0.001100 0.028319	0.002668 1.000000	
dhl	-2.93E-05 -0.047368	5.79E-06 0.005795	0.043264 0.036388	0.002394 0.068629	0.000376 0.026773	0.001013 0.044804	-1.27E-05 -0.008187	0.000905 1.000000

Table 4: Covariance and correlation among series

Table 4 shows how the series are correlated to each other without employing any econometric models. The relationship between Bitcoin and Litecoin return is fairly strong. The positive correlation indicates both returns are moving in the same direction on average. Transaction volume between Bitcoin and Litecoin has the strongest positive correlation. Wikipedia views between Bitcoin and Litecoin has smaller positive correlation. Both transaction volumes are strongly correlated with Litecoin Wikipedia view but weakly correlated with Bitcoin Wikipedia view. Although the magnitude is very small but the correlation indicates Bitcoin and Litecoin hashrates have negative correlation. None of the series have strong correlation with Bitcoin and Litecoin returns by examining the correlation relationship.

3.7. Hypothesis expectation

Three null hypotheses are given in order to examine the research questions in three aspects. The first hypothesis examines whether there exists a relationship between lags of Bitcoin or Litecoin returns on their current returns. The second hypothesis examines whether there exist common factors influencing both Bitcoin and Litecoin current returns. The third hypothesis examines the volatility transmission to observe the contagion and spill-over effects. The following BEKK model shows the conditional mean equations for Bitcoin and Litecoin returns.

Conditional mean equations for Bitcoin and Litecoin returns:

$$\begin{aligned} r_{b,t} = c_1 &+ \varphi_{11} lr_{b,t-1} + \varphi_{12} lr_{b,t-2} + \tau_{11} lr_{l,t-1} + \tau_{12} lr_{l,t-2} \\ &+ \phi_{11} w_{b,t-1} + \phi_{12} w_{l,t-1} + \gamma_{11} lv_{b,t-1} + \gamma_{12} lv_{l,t-1} \\ &+ \delta_{11} dh_{b,t-1} + \delta_{12} dh_{l,t-1} + \lambda_{11} \sigma^2_{b,t-1} + \lambda_{12} \sigma_{bl,t-1} \\ &+ \lambda_{13} \sigma^2_{l,t-1} + \varepsilon_{b,t} \end{aligned}$$

Equation 3.6.1

$$\begin{aligned} r_{l,t} = c_2 &+ \varphi_{21} lr_{l,t-1} + \varphi_{22} lr_{l,t-2} + \tau_{21} lr_{b,t-1} + \tau_{22} lr_{b,t-2} \\ &+ \phi_{21} w_{b,t-1} + \phi_{22} w_{l,t-1} + \gamma_{21} lv_{b,t-1} + \gamma_{22} lv_{l,t-1} \\ &+ \delta_{21} dh_{b,t-1} + \delta_{22} dh_{l,t-1} + \lambda_{21} \sigma^2_{b,t-1} + \lambda_{22} \sigma_{bl,t-1} \\ &+ \lambda_{23} \sigma^2_{l,t-1} + \varepsilon_{l,t} \end{aligned}$$

Equation 3.6.1.2

Where c_1 and c_2 are the constant terms, φ_{ij}, τ_{ij}, ϕ_{ij}, γ_{ij}, δ_{ij} are the coefficient parameters for lag of returns, Wikipedia views, transaction volume and growth of hashrate for Bitcoin and Litecoin, where i,j=1 or 2. The parameters λ_{ij} capture the variance and covariance for Bitcoin and Litecoin return, for i=1,2 and j=1,2 and 3.

3.7.1. First hypothesis

a) **H_0: There does not exist significant relationship between returns of Bitcoin and Litecoin**

An alternative hypothesis is that there exists significant relationship between returns of Bitcoin and Litecoin. If the evidence supports an alternative hypothesis, then φ_{ij} coefficients should be significant which are used to examine whether Bitcoin and Litecoin markets are efficient. If $\boldsymbol{\varphi_{11}}$ and $\boldsymbol{\varphi_{12}}$ are significant, then Bitcoin market is not efficient because the past returns have predictive power on current returns. If $\boldsymbol{\varphi_{21}}$ and $\boldsymbol{\varphi_{22}}$ are significant, then Litecoin market is not efficient. The coefficients τ_{ij} are used to examine the causality relationship between Bitcoin and Litecoin returns. If $\boldsymbol{\tau_{11}}$ or $\boldsymbol{\tau_{12}}$ is significant, then there exist Granger causality from the lag of Litecoin return on Bitcoin current return. If $\boldsymbol{\tau_{21}}$ or $\boldsymbol{\tau_{22}}$ is significant, then there exist Granger causality from the lag of Bitcoin returns on Litecoin current return.

Bitcoin being the first decentralized cryptocurrency, has the largest capitalization in the cryptocurrency market. Many cryptocurrencies have different features to Bitcoin, but the main feature of decentralization is the same. Bitcoin could be seen as a market leader while other cryptocurrencies could be seen as followers or substitutes/competitors to Bitcoin. Therefore, it is expected to see that lags of Bitcoin returns to have a positive impact on Litecoin returns ($\boldsymbol{\tau_{21}}, \boldsymbol{\tau_{22}} > 0$) and its influence on Litecoin return is greater than the influence of lags of Litecoin return on Bitcoin return ($\boldsymbol{\tau_{21}} > \boldsymbol{\tau_{11}}$and $\boldsymbol{\tau_{22}} > \boldsymbol{\tau_{12}}$). Impact of lags of Litecoin returns on Bitcoin return could be negative or positive. A negative effect might suggest Litecoin acts as a competitor with Bitcoin ($\boldsymbol{\tau_{11}} < 0$ and $\boldsymbol{\tau_{12}} < 0$). In another word, an increase of demand of Litecoin will decrease the demand for Bitcoin. While a positive effect might suggest, Litecoin is a follower of Bitcoin ($\boldsymbol{\tau_{11}} > 0$ and $\boldsymbol{\tau_{12}} > 0$). An increase of demand for Litecoin will also increase demand for Bitcoin. Granger causality relationship exists if at least one coefficient of $\boldsymbol{\tau_{ij}}$ is significant.

3.7.2. Second hypothesis

b) H_0: There does not exist common factors that could affect both Bitcoin and Litecoin returns

The null hypothesis suggests none of the exogenous variables has an impact on Bitcoin and Litecoin returns. The alternative hypothesis suggests at least one of the exogenous variables has impact on Bitcoin and Litecoin current returns. In the following, comments will be given if there exists enough evidence to support an alternative hypothesis.

Wikipedia views

The coefficients $\boldsymbol{\phi_{ij}}$ represents the effect of the number of Wikipedia views on Bitcoin and Litecoin which indicate the popularity of cryptocurrencies. Therefore, $\boldsymbol{\phi_{11}}$ and $\boldsymbol{\phi_{22}}$ are expected to be positively related. An increase in the number of searches on Wikipedia website could potentially lead to an increase in demand in cryptocurrencies because more people know the existence of cryptocurrencies. However, the cross effects are expected to have opposite influence on Bitcoin and Litecoin returns such that Bitcoin and Litecoin Wikipedia views are expected to have positive and negative effect on Litecoin and Bitcoin returns respectively. Since Bitcoin is the fist decentralized cryptocurrency, people are likely to search for Bitcoin when they first explore cryptocurrency. Once they have an idea of cryptocurrency, they might explore the cryptocurrency market further by searching other cryptocurrencies such as Litecoin. Therefore, an increase in Bitcoin Wikipedia view is expected to have a positive impact on Litecoin return because it will increase the chance of people searching for Litecoin on Wikipedia. Some people who searched for Litecoin might be interested in holding Litecoin. It is reasonable to assume that many of this type of people have previously held other cryptocurrency such as Bitcoin because it was the first decentralized cryptocurrency which was first known to the world. They could either invest more money in Litecoin or sell Bitcoin in exchange for Litecoin which could lead to drop in Bitcoin price and return in the latter case.

Transaction volume

The coefficients $\boldsymbol{\gamma_{ij}}$ represent the effect of transaction volume of Bitcoin and Litecoin in US dollar at BTC-e exchange market. Both $\boldsymbol{\gamma_{11}}$ and $\boldsymbol{\gamma_{22}}$ coefficients are expected to be significant which implies transaction volumes are expected to have a significant impact on returns for Bitcoin and Litecoin.

Chen et al., (2001) suggest trading volume is positively related to stock return which is in line with Karpoff (1987) who also found a positive correlation between trading volume and stock return.

If Bitcoin and Litecoin are being treated as currencies, then $\boldsymbol{\gamma_{11}}$ and $\boldsymbol{\gamma_{22}}$ are expected to be positive. The decrease in transaction cost is expected to increase demand for the cryptocurrency. Hence lead to raises in returns for Bitcoin and Litecoin. The cross effect of transaction volumes between Bitcoin and Litecoin on their current returns are expected to be negative because they both serve the same purpose in terms of currency. An increase in transaction volume in one cryptocurrency lead to decrease in transaction cost which will be an advantage for that cryptocurrency. Hence, the demand will be further increased as people prefer to use a currency with lower transaction cost. (Details explanation why this is the case)

If Bitcoin and Litecoin are being treated as investment assets, then $\boldsymbol{\gamma_{11}}$ and $\boldsymbol{\gamma_{22}}$ could either be positive or negative. Speculators who hold such risky assets will hope the price to raise in the future so that they could sell the assets for profits. Therefore, an increase in transaction volume might correspond to an increase in the supply of cryptocurrencies in exchange market which reduces the price and returns for cryptocurrencies. On the other hand, speculators who expect price of such assets will raise in the future will lead to increase in demand.

Hashrate

The growth of hashrates is represented by $\boldsymbol{\delta_{ij}}$ coefficients, which are expected to have positive impacts on Bitcoin and Litecoin current returns when $i = j$. The growth of hashrates is equivalent to growth of difficulty level for mining cryptocurrencies. The change in difficulty could be affected by two aspects including the change in the number of miners and development in mining technology. Development in mining machine leads to improvement of mining technology which is changed over a long period of time instead of daily change. Therefore, this study assumes mining technology remains constant for the examined sample period. The change in the number of miners is assumed to be the only factor that affects the level of difficulty of mining cryptocurrencies. Miners' incentive is to make a profit via mining reward and transaction fees. Some miners expect the values of cryptocurrencies they receive are going to raise in the future. Therefore, they will hold the cryptocurrencies instead of exchanging them for fiat currency immediately. In another word, the growth of hashrates could be seen as the increase in the number of miners who expect Bitcoin or Litecoin returns will raise. In addition, the increase in the number of miners will strengthen the security of cryptocurrency network from majority attack and reduce the confirmation waiting time for each transaction. Such benefits might lead to higher demand on Bitcoin and Litecoin in the exchange market. Therefore, it also implies an increase in demand from Bitcoin new users who were attracted by these benefits. Given that supply of both Bitcoin and Litecoin are predetermined in the way that the number of newly generated cryptocurrencies are halved within a certain period of time with total supply being fixed. Therefore, an increase in demand will lead to a rise in the price for Bitcoin and Litecoin. It is expected that $\boldsymbol{\delta_{ii}}$ are positive significant. In another word, an increase in the growth of hashrates will lead to increase in Bitcoin, and Litecoin returns.

If Litecoin is a substitution of Bitcoin, then $\boldsymbol{\delta_{12}}$ coefficient will not be expected to be significant. However, $\boldsymbol{\delta_{21}}$ is expected to be positively significant because Bitcoin is the market leader which will have a significant influence on followers such as Litecoin.

Out of thousands of cryptocurrencies, If Litecoin is an alternative cryptocurrency that can compete with Bitcoin. Then $\boldsymbol{\delta_{12}}$ and $\boldsymbol{\delta_{21}}$ are expected to be negatively significant. As described above, an increase in growth of hashrates suggests an increase in demand for cryptocurrency. If two cryptocurrencies are competing for each other, then such increase in demand of one cryptocurrency will lead to a decrease in demand of another cryptocurrency. As a competitor, Litecoin is expected to have equal influence on Bitcoin. As the first decentralized cryptocurrency, Bitcoin has define cryptocurrency with some fundamental features. As cryptocurrency market evolves, many other cryptocurrencies were created with the same fundamental cryptocurrency features such as decentralizing and added some new features. It is easier to survive from the cryptocurrency market if the additional feature can attract users or investors. For instance, Litecoin changed the protocol by reducing the block time which means it is quicker to mine Litecoin than Bitcoin on average. One of the main features of Bitcoin is the anonymous feature. Even though people cannot track who is holding the Bitcoin, but all the transaction could be viewed by anyone in the network via public ledger. Another cryptocurrency, Zerocash, changes the way that payment transactions are assembled and verified and improves the anonymous feature by revealing neither the payment origin, destination nor amount. Therefore Bitcoin feature might not be able to fulfil the needs of everyone which gives the opportunity for other cryptocurrencies to attract users or investors. Therefore, another cryptocurrency might take Bitcoin's market place when it falls because most of them have the most fundamental features including decentralization. As a competitor, the increase in demand of one cryptocurrency might lead to decrease in demand of another cryptocurrency if some bad/good news about one cryptocurrency has been released.

3.7.3. Third hypothesis

c) **H_0: There does not exist significant volatility transmission between Bitcoin and Litecoin**

The null hypothesis suggests there is no volatility transmission between Bitcoin and Litecoin markets which means neither direct nor indirect volatility transmission exist between these two markets. This hypothesis could be examined in two aspects: volatility contagion and volatility spillover effect between Bitcoin and Litecoin markets. For direct volatility transmission, if the return volatility from one cryptocurrency could lead to change in return for another cryptocurrency. Then there exists volatility contagion. If the past volatility of one cryptocurrency affects the current volatility of another cryptocurrency. Then there exists volatility spillover effect. If covariance of Bitcoin and Litecoin return in the past affect current return and current volatility of another cryptocurrency. Then there exists indirect volatility transmission.

In conditional mean equation (1) and (2), λ_{13}, λ_{21} represent the volatility transmission directly from Litecoin and Bitcoin markets on the returns of Bitcoin and Litecoin respectively. Whereas λ_{12} , λ_{22} represent the indirect volatility transmission on Bitcoin and Litecoin returns respectively.

If Bitcoin is the market leader while Litecoin is a follower of Bitcoin. Then λ_{12}, λ_{13} are not expected to be significant because the effect of follower on market leader would be too small to have an impact given that the capitalization of Litecoin is much smaller than the capitalization of Bitcoin. However, λ_{21} and λ_{22} are expected to be positive. The increase in uncertainty of Bitcoin market corresponds to increase of risk in Bitcoin market. As the market leader, Bitcoin price could be affected by many events and factors. As it is the first decentralized cryptocurrency, Bitcoin system is not perfect which has been questioned in many aspects before. For instance, some exchange markets have been attacked by hackers which cause some Bitcoin users to lose faith in Bitcoin. Increase in risk of Bitcoin market might affect all other cryptocurrency markets by reducing the demand for these cryptocurrencies in order to avoid risk. Therefore, λ_{21} is expected to be negative. Moreover, λ_{22} is expected to be positive because as a follower, Litecoin return is expected to move in the same direction as Bitcoin return.

If Litecoin competes with Bitcoin, then λ_{21} and λ_{13} are expected to be positive. For risk-adverse investors, an increase of uncertainty in Bitcoin or Litecoin market will lead to increase in demand of Litecoin or Bitcoin which raise the returns of Litecoin and Bitcoin respectively. Out of thousands of cryptocurrencies, if Litecoin could compete with Bitcoin, then it implies Litecoin has the potential of taking Bitcoin's place when Bitcoin fails. Therefore, when demand for Bitcoin changes, the demand for Litecoin will also change but in opposite direction. Therefore, the returns for Bitcoin and Litecoin are expected to move in the opposite direction, $\lambda_{22} < 0$.

For conditional variance-covariance equation, only BEKK model could measure the cross-effect of volatility transmission between Bitcoin and Litecoin markets. If there exist volatility transmission from Litecoin market to Bitcoin market, then the parameters for lag of ARCH and GARCH terms for Litecoin conditional variance equation are expected to be significant, vice versa. The indirect volatility transmission is found in the conditional variance and covariance equations. If there exist indirect volatility transmission from Litecoin market to the Bitcoin market. Then the coefficients for the covariance term should be significant in explaining the Bitcoin conditional variance at current time.

This study speculates that the size of capitalization does not play an important role in this case. Instead, this study speculates technology and features of each cryptocurrency might have greater influence. Bitcoin and Litecoin share two of the main features including decentralization and anonymous. Therefore, if one cryptocurrency is being questioned, then another cryptocurrency will likely be questioned too.

3.8. Results

With the maximum allowed lag length chosen to be seven for both endogenous and exogenous variables, the optimal lag length for VARX model is based on Schwarz information criteria which give the smallest value of -9.28. The test results are presented in the following Table 5. Past volatility is considered in the conditional mean equation such that GARCH term is included which is determined by past residual squared and past variance. Since the estimated model is in multivariate form, the dynamic relationship between Bitcoin and Litecoin returns could be examined. The conditional variance covariance would be estimated by BEKK model which allow examining the transmission of volatilities between Bitcoin and Litecoin. In addition, DCC model would be estimated in order to examine the dynamic conditional correlation between them. By computing the Hosking (1981) variant of multivariate Q statistic where the null hypothesis is that autocorrelation and lagged cross-correlation are both zero. Test statistics for BEKK and DCC models were given 55.47444 and 64.77202 when maximum lag length was chosen to be seven. Results suggest none of these models rejects the null hypothesis of no autocorrelation at 5% significant level. Lagrange multiplier test was employed in testing multivariate ARCH effects. The null hypothesis is that standardized residual series have mean zero and they are not serially correlated along with a fixed covariance matrix. The test statistics of multivariate ARCH tests for BEKK and DCC are 41.85 and 32.40 respectively, which show lack of evidence to reject the null hypothesis. Therefore, results suggest there does not exist volatility clustering after employing BEKK and DCC model. Robust standard errors have been employed in quasi-maximum likelihood approach in order to obtain estimated results.

	P=1	P=2	P=3	P=4	P=5	P=6	P=7
Q=1							
AIC	-9.329	-9.323	-9.331	-9.336	-9.343	-9.347	-9.336
SBC	-9.266	-9.228	-9.204	-9.178	-9.153	-9.146	-9.135
Hannan-Quinn	-9.305	-9.287	-9.282	-9.276	-9.270	-9.270	-9.259
(log) FPE	-9.329	-9.323	-9.331	-9.336	-9.343	-9.347	-9.336
Q=2							
AIC	-9.354	-9.350	-9.358	-9.364	-9.371	-9.374	-9.365
SBC	-9.280	-9.245	-9.221	-9.196	-9.170	-9.163	-9.153
Hannan-Quinn	-9.326	-9.310	-9.305	-9.300	-9.294	-9.294	-9.284
(log) FPE	-9.354	-9.350	-9.358	-9.364	-9.371	-9.374	-9.365
Q=3							
AIC	-9.351	-9.347	-9.359	-9.364	-9.370	-9.373	-9.363
SBC	-9.266	-9.231	-9.211	-9.185	-9.159	-9.151	-9.141
Hannan-Quinn	-9.318	-9.303	-9.302	-9.295	-9.289	-9.288	-9.278
(log) FPE	-9.351	-9.347	-9.358	-9.364	-9.370	-9.373	-9.363
Q=4							
AIC	-9.352	-9.349	-9.361	-9.375	-9.380	-9.383	-9.367
SBC	-9.257	-9.222	-9.203	-9.185	-9.159	-9.150	-9.134
Hannan-Quinn	-9.316	-9.300	-9.301	-9.302	-9.296	-9.294	-9.278
(log) FPE	-9.352	-9.349	-9.361	-9.374	-9.380	-9.383	-9.367
Q=5							
AIC	-9.356	-9.354	-9.369	-9.380	-9.390	-9.392	-9.375
SBC	-9.251	-9.217	-9.200	-9.179	-9.157	-9.149	-9.131
Hannan-Quinn	-9.316	-9.302	-9.304	-9.303	-9.301	-9.299	-9.282
(log) FPE	-9.356	-9.354	-9.369	-9.380	-9.390	-9.392	-9.375
Q=6							
AIC	-9.360	-9.358	-9.373	-9.383	-9.391	-9.397	-9.382
SBC	-9.244	-9.210	-9.193	-9.171	-9.148	-9.144	-9.128
Hannan-Quinn	-9.316	-9.301	-9.304	-9.302	-9.299	-9.301	-9.285
(log) FPE	-9.360	-9.358	-9.373	-9.383	-9.391	-9.397	-9.382
Q=7							
AIC	-9.358	-9.357	-9.373	-9.381	-9.390	-9.395	-9.383
SBC	-9.231	-9.198	-9.182	-9.159	-9.136	-9.131	-9.118
Hannan-Quinn	-9.310	-9.296	-9.300	-9.296	-9.293	-9.294	-9.282
(log) FPE	-9.358	-9.357	-9.373	-9.381	-9.389	-9.395	-9.383

Table 5: Information criteria for VARX model

3.8.1. Model A:VARX(2,1)-MGARCH(1,1)-Mean-BEKK

Table 6 represents the results of the estimated model. In the following, estimated conditional mean model and estimated conditional variance covariance model would be discussed in detail separately. Four hypotheses would be discussed along with the results where the first three hypotheses would be discussed when interpreting results for the conditional mean model. The fourth hypothesis would be discussed in both conditional mean and variance covariance model since it could be examined from both models.

Variable	Parameters	Coefficients	Standard Error	p-value
Conditional Mean Model(LRB)				
1. $lr_{b,t-1}$	φ_{11}	0.1496[a]	0.021	0.000
2. $lr_{b,t-2}$	φ_{12}	0.0099	0.025	0.700
3. $lr_{l,t-1}$	τ_{11}	-0.0636 [a]	0.011	0.000
4. $lr_{l,t-2}$	τ_{12}	0.0308[b]	0.014	0.032
5. Constant		-0.0006 [b]	0.000	0.013
6. $w_{b,t-1}$	ϕ_{11}	0.014	0.012	0.242
7. $w_{l,t-1}$	ϕ_{12}	-1.394 [a]	0.356	0.000
8. $lv_{b,t-1}$	γ_{11}	0.0011 [a]	0.000	0.000
9. $lv_{l,t-1}$	γ_{12}	-0.0006 [a]	0.000	0.000
10. $dh_{b,t-1}$	δ_{11}	-0.0015	0.007	0.823
11. $dh_{l,t-1}$	δ_{12}	0.0158	0.009	0.109
12. $\sigma^2_{b,t-1}$	λ_{11}	4.7357 [a]	0.402	0.000
13. $\sigma_{bl,t-1}$	λ_{12}	0.9487 [a]	0.268	0.000
14. $\sigma^2_{l,t-1}$	λ_{13}	-0.2028	0.131	0.121
Mean Model(LRL)				
15. $lr_{b,t-1}$	τ_{21}	0.6204 [a]	0.015	0.000
16. $lr_{b,t-2}$	τ_{22}	0.2943 [a]	0.020	0.000
17. $lr_{l,t-1}$	φ_{21}	-0.3154 [a]	0.020	0.000
18. $lr_{l,t-2}$	φ_{22}	-0.0671 [a]	0.025	0.007
19. Constant		-0.0081 [a]	0.0002	0.000
20. $w_{b,t-1}$	ϕ_{21}	0.0024	0.013	0.854
21. $w_{l,t-1}$	ϕ_{22}	0.2934	0.404	0.465
22. $lv_{b,t-1}$	γ_{21}	-0.0037 [a]	0.000	0.000
23. $lv_{l,t-1}$	γ_{22}	0.0022 [a]	0.000	0.000
24. $dh_{b,t-1}$	δ_{21}	0.0088	0.006	0.155
25. $dh_{l,t-1}$	δ_{22}	0.0145 [c]	0.008	0.070
26. $\sigma^2_{b,t-1}$	λ_{21}	13.1070 [a]	0.505	0.000
27. $\sigma_{lb,t-1}$	λ_{22}	-4.5417 [a]	0.429	0.000
28. $\sigma^2_{l,t-1}$	λ_{23}	0.5794 [a]	0.222	0.009
Conditional Variance-Covariance Model				
29. C(1,1)		0.0041 [a]	0.000	0.000
30. C(2,1)		-0.0003	0.000	0.158
31. C(2,2)		0.0025 [a]	0.000	0.000

32. A(1,1)	0.3572 [a]	0.007	0.000
33. A(1,2)	-0.2531 [a]	0.014	0.000
34. A(2,1)	0.0453 [a]	0.004	0.000
35. A(2,2)	0.6337 [a]	0.006	0.000
36. B(1,1)	0.9001 [a]	0.002	0.000
37. B(1,2)	0.0814 [a]	0.003	0.000
38. B(2,1)	0.0107 [a]	0.001	0.000
39. B(2,2)	0.8570 [a]	0.002	0.000

Table 6: Estimated results for BEKK model. Note that superscript letter a, b and c represent 1%, 5% and 10% significant levels respectively.

3.8.1.1. Conditional mean equation

The following estimated conditional equations are shown to facility the discussion.

$$\begin{aligned} r_{b,t} = & -0.0006^{(b)} + 0.1496^{(a)} lr_{b,t-1} + 0.0099 lr_{b,t-2} \\ & - 0.0636^{(a)} lr_{l,t-1} + 0.0308^{(b)} r_{l,t-2} + 0.00001 w_{b,t-1} \\ & - 0.0014^{(a)} w_{l,t-1} + 0.0011^{(a)} lv_{b,t-1} \\ & - 0.0006^{(a)} lv_{l,t-1} - 0.0015 dh_{b,t-1} + 0.0158 dh_{l,t-1} \\ & + 4.7357^{(a)} \sigma^2_{b,t-1} + 0.9487^{(a)} \sigma_{bl,t-1} - 0.2028 \sigma^2_{l,t-1} \\ & + \varepsilon_{b,t} \end{aligned}$$

Equation 3.8.1.1.1

$$\begin{aligned} r_{l,t} = & -0.0081^{(a)} - 0.3154^{(a)} lr_{l,t-1} - 0.0671^{(a)} lr_{l,t-2} \\ & + 0.6204^{(a)} lr_{b,t-1} + 0.2943^{(a)} lr_{b,t-2} \\ & + 0.00001 w_{b,t-1} + 0.0003 w_{l,t-1} \\ & - 0.0037^{(a)} lv_{b,t-1} + 0.0022^{(a)} lv_{l,t-1} \\ & + 0.0088 dh_{b,t-1} + 0.0145^{(c)} dh_{l,t-1} \\ & + 13.107^{(a)} \sigma^2_{b,t-1} - 4.542^{(a)} \sigma_{bl,t-1} \\ & + 0.579^{(a)} \sigma^2_{l,t-1} + \varepsilon_{l,t} \end{aligned}$$

Equation 0

Note: Superscript letter a, b and c represent 1%, 5% and 10% significant levels respectively.

3.8.1.1.1. Endogenous variables

The results from the last chapter suggest lagged of returns are significant in predicting the its own current returns for Bitcoin market. The endogenous variables in this section could examine the causality relationship between Bitcoin and Litecoin. This section discusses the first two hypotheses by examining market efficiency for Bitcoin and Litecoin and whether there exists causality relationship between their returns. Both first and second lags of returns for both Bitcoin and Litecoin were used to examine whether Bitcoin and Litecoin markets are efficient via coefficients φ_{ij} where i,j=1,2. The coefficient $\varphi_{11} = 0.1496$ is positively related indicating first lag of Bitcoin return is significant in predicting current Bitcoin return at 1% significant level. An increase of 1% of first lag of Bitcoin return will lead to an increase of 0.149% increase in current Bitcoin return. Both φ_{21} and φ_{22} are negatively significant at 1% significant level. Results suggest an increase of 1% in first and second lags of Litecoin return will lead to a decrease of 0.32% and 0.07% in Litecoin current return respectively. Results suggest neither Bitcoin nor Litecoin markets are efficient since lag of their returns were significant in predicting their current returns. The coefficient on the first lag of Litecoin return on its own current return is greater than the first lag of Bitcoin return on its own current return. Even though the second lag of Litecoin return is significant at 1% level, but the absolute value is very close to zero which also suggests that lags of returns are not persistent in both conditional mean equations.

Causality relationship could be examined via τ_{ij} coefficients where i, j=1, 2. Both $\tau_{11} = -0.064$ and $\tau_{12} = 0.031$ were significant indicating both first and second lags of Litecoin return granger cause Bitcoin current return. An increase of 1% in the first and second lag of Litecoin return will lead to a decrease of 0.06% and an increase of 0.03% in Bitcoin current return respectively. As shown in the results, lags of Litecoin returns have opposite effect on Bitcoin current return. One reason to explain such a result is that Bitcoin is the first decentralized cryptocurrency while Litecoin and other hundreds of cryptocurrencies were created similar to Bitcoin. Litecoin has value because it has a preferable feature to Bitcoin. However, how much these features worthy is not clear. Therefore, holding Litecoin is risky when the price is increased which would lead to selling of Litecoin. Hence, the increase of Litecoin return in the past would lead to the decrease of Litecoin current return.

In addition, both lags of Bitcoin returns are also significant in explaining Litecoin current return. Therefore, there exist bi-directional causality relationship between Bitcoin and Litecoin returns. By calculating the long run effect of Bitcoin return on Litecoin and vice versa. The influence of Bitcoin return on Litecoin return is 2.3913[9] in absolute value when compared to

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[9] The value for measuring the influence is calculated by the following: |-0.3154-

the influence of Litecoin return on Bitcoin return is 0.039. Hence, the influence of Bitcoin on Litecoin return is greater than the influence of Litecoin return on Bitcoin return in the long run.

This might be due to the fact that Bitcoin as the first and most popular cryptocurrency in the world, it has drawn more attention from the world than other cryptocurrencies including Litecoin. One of the main technology in cryptocurrency, decentralization, is created by Bitcoin. This technology also defines cryptocurrency as a currency that does not need a trusted third party to exist in order to make a transaction. Therefore, newly generated cryptocurrencies could add or modify some features, but the decentralization feature is always maintained. Even though Bitcoin might not have a preferable feature like other cryptocurrencies, but it presents the standard version of cryptocurrencies. Therefore, it is not surprising that Bitcoin has a greater cross effect on Litecoin return while Litecoin has less cross effect on Bitcoin return. However, it is interesting to note that first and second lags of Litecoin return have opposite impacts on Bitcoin current return. An increase in Litecoin return suggests an increase of Litecoin price is due to increase in demand since the supply of Litecoin is predetermined. Such an increase in demand could be due to different reasons including Litecoin is being accepted by more merchants, Litecoin became easier to mine and so on. Therefore, it is possible that people are switching from Bitcoin or other cryptocurrencies into Litecoin by selling Bitcoin which lead to a decrease in Bitcoin price. However, it would not be persistence. For a longer period of time, acceptance of Litecoin would suggest acceptance of cryptocurrency market for users, which lead to increase of demand in cryptocurrencies including Bitcoin. Hence, $\boldsymbol{\tau_{12}}$ is positively related rather than negative. Therefore, results support expectation and fully confirm that both first and second hypotheses were valid.

In order to examine how past returns of one cryptocurrency affect the current return of another cryptocurrency. An impulse response of Bitcoin and Litecoin returns on Bitcoin and Litecoin returns shocks are plotted in graph 1. As the graph shows that 1% of a positive shock of Bitcoin and Litecoin returns on their own returns will lead to increase of 0.02% and 0.025% positive changes respectively. However, these shocks have significant negative effects on both

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0.0671|$\Delta lr_{l,t}$=|0.6204+0.2943|$\Delta lr_{b,t}$ → $\Delta lr_{l,t}/\Delta lr_{b,t}$=2.3913. In the long run, the first and second lag of returns are the same.

Bitcoin, and Litecoin returns after period-1 and the effect gradually become insignificant after period-2. One percent shock of Bitcoin return will lead to 0.018% positive change in Litecoin return. The effect of the shock gradually decreases and becomes insignificant on period-2. However, the shock leads to a negative effect on Litecoin return on period-3 and immediately becomes insignificant in the following period. One percent shock of Litecoin return does not lead to any impact on Bitcoin return in period-0. The shock leads to a negative effect and positive effect on Bitcoin return in period-1 and period-2 respectively. This might suggest an increase in demand for Litecoin increases will attract more people to sell Bitcoin which lower the Bitcoin return. After Bitcoin price decreases, more people will purchase Bitcoin at a lower price which increases the demand for Bitcoin, hence increase the Bitcoin return.

3.8.1.1.2. Exogenous variables

This section discusses the third hypothesis by examining whether Wikipedia view, transaction volume and growth of hashrates were significant in predicting Bitcoin and Litecoin current returns. In summary, Transaction volumes variables for both Bitcoin and Litecoin have a larger influence on Bitcoin and Litecoin returns than other two variables. Both Wikipedia views and growth of hashrates variables have only one related coefficient that is significantly different from zero, which show lack of evidence in supporting the third hypothesis. Therefore, the third hypothesis is only partially confirming since only transaction volume variable is significant in explaining both Bitcoin and Litecoin current returns.

In the following, only the significant variables would be reported. Results on Wikipedia view variables suggest an increase of 1000,000 Wikipedia views for Litecoin will lead to decrease of Bitcoin return by 0.014%. This result agrees to the expectation. Results on transaction volume suggest both Bitcoin and Litecoin transaction volume are significant at 1% level in explaining current returns for Bitcoin and Litecoin. The coefficients γ_{11} and γ_{22} indicates a 1% increase of transaction volume for Bitcoin and Litecoin in the last period will lead to increase of 0.001% and 0.002% increase in current returns for Bitcoin and Litecoin respectively. As expected, such results might suggest Bitcoin and Litecoin are being treated as currency because the increase in transaction volume will increase liquidity which would lower transaction cost when purchasing Bitcoin or Litecoin. Provided the volatility of Bitcoin and Litecoin are highly volatile for the examined period of time. Users who treat them as currency might prefer to purchase cryptocurrencies when they need them. Since Bitcoin and Litecoin could be used in daily life. A reduce in transaction cost in exchange market has a significant influence on users. For the same reason, γ_{12} and γ_{21} are negatively significant because users prefer a cryptocurrency that has lower transaction cost. For instance, an increase in transaction volume for Litecoin would reduce the transaction cost for purchasing Litecoin. Therefore, the demand for Bitcoin will be decreased if transaction volume for Bitcoin is at the same level. A decrease in Bitcoin transaction volume will lead to decrease in Bitcoin price. As expected, Bitcoin transaction volume has a larger impact on Litecoin return, which could be explained by the difference in their market capitalization. Litecoin which has much smaller market capitalization is harder to affect Bitcoin return. The growth of hashrates of Litecoin has a significant positive impact on its own return at 10% level which is expected. The result indicates an increase of 1% in growth of hashrates will lead to increase of 0.015% in Litecoin return.

Furthermore, a few graphs have been plotted for multiplier analysis which shows how Bitcoin and Litecoin returns respond to shock from exogenous variables. The second and third graphs (graph-2 and graph-3) represent the response of Bitcoin and Litecoin returns on transaction volumes shocks. A unit shock Bitcoin transaction volume does not lead to any changes in both Bitcoin and Litecoin in the first period. The response of Bitcoin return remains insignificant until period-3 where there is a negative effect on Bitcoin return. However, this effect immediately disappears in period-4. Litecoin return responds to Bitcoin transaction volume shock in period-2 which indicates a slight increase in Litecoin return. However, such positive effect disappears within one period. In period-4, such shock has a negative impact on Litecoin return, but the magnitude of changes is very small. Bitcoin return is not responding to Litecoin transaction volume in the first period either. However, the shock leads to a negative and positive shock in period-2 and period-3 respectively. There is an immediate respond of Litecoin return to Litecoin transaction volume shock. Graph-3 indicates the shock leads to 0.00006-unit positive change in Litecoin return which is very small. The effect of shock continues to affect Litecoin return in the following two periods. Litecoin return becomes negatively affected by its own transaction volume shock in period-2 and period-3. Before the shock effect disappears in period-5, there is a positive effect on Litecoin return again, but the influence is very tiny.

The fourth and fifth graphs show responses of Bitcoin and Litecoin returns on hashrates shocks. Both Bitcoin and Litecoin respond positively to Bitcoin hashrate in period-1. The positive effect died away quickly and changed into negative effects in period-2 and period-3 before it becomes insignificant in period-4. The effect on Litecoin return stays a period longer which dies away gradually in period-3. But there also has a negative effect on Litecoin return from the shock in period-4. The graph shows Bitcoin hashrate shock is more persistence on Litecoin return. The last graph shows the effect of Litecoin hashrate does not have a significant impact on both Bitcoin and Litecoin for two periods and three periods respectively. The only significant period that Bitcoin and Litecoin returns respond to Litecoin hashrate shock are in period-3 and period-4 respectively. Negative effects could be found in these two periods. In summary, Litecoin hashrates have less influence on both Bitcoin and Litecoin returns. Litecoin return is more sensitive to Hashrates which makes the shocks more persistence.

3.8.1.1.3. Volatility

The final hypothesis could be examined in two parts. The first part is straight forward which examine whether there exists volatility transmission between two cryptocurrency markets and affecting each others' current returns. The second part investigates volatility transmission by considering the past information of each cryptocurrency markets and past volatilities to see how past information and volatilities of one cryptocurrency market are transmitted into another cryptocurrency market. In this section, the first part will be discussed.

The estimated variance and covariance of Bitcoin and Litecoin on conditional mean equation help to examine the relationship between volatility and return for Bitcoin and Litecoin. Results indicate Bitcoin return is affected by its own volatility and indirectly affected by Litecoin volatility via covariance between these two. However, Litecoin return is affected by both Bitcoin and Litecoin volatilities as well as the covariance between these two. The increase of uncertainty of Bitcoin market will lead to increase in both Bitcoin, and Litecoin returns. Litecoin return is more sensitive to Bitcoin volatility since $|\lambda_{21}| > |\lambda_{13}|$. The increase of uncertainty within Litecoin market also increase the Litecoin return but only for a small amount compare to Bitcoin volatility since $|\lambda_{21}| > |\lambda_{13}| > |\lambda_{23}|$. Therefore, volatility of Bitcoin has a greater impact than Litecoin volatility.

Moreover, the negative covariance between Bitcoin and Litecoin return in the second conditional mean equation suggest there exist co-movement between two cryptocurrencies and they are moving in opposite direction on average. The magnitude of the negative covariance is large which implies Bitcoin and Litecoin returns have large changes in the opposite direction. In addition, the sign of covariance in the first conditional mean equation is positive. In order to further investigate the dynamic relationship, both conditional variance equations from multivariate GARCH-BEKK and DCC models would be examined where the correlation will be taken into account which provides more details of the co-movement of Bitcoin and Litecoin returns. Results might suggest that Litecoin market is not as popular as Bitcoin. The number of users and amount of capital flow within Litecoin market is much smaller than Bitcoin market. Therefore, volatility transmission is unidirectional which only being transmitted from Bitcoin to Litecoin.

3.8.1.2. Conditional variance equation for BEKK model

The following three equations are obtained by multiplying out the conditional variance-covariance-BEKK from matrix form.

$$\begin{aligned}\sigma^2{}_{b,t} = {} & 1.68 * 10^{-5^{(a)}} + 0.128^{(a)}\varepsilon^2{}_{b,t-1} - 0.18^{(a)}\varepsilon_{b,t-1}\varepsilon_{l,t-1} \\ & + 0.064^{(a)}\varepsilon^2{}_{l,t-1} + 0.81^{(a)}\sigma^2{}_{b,t-1} + 0.147^{(a)}\sigma_{bl,t-1} \\ & + 0.007^{(a)}\sigma^2{}_{l,t-1}\end{aligned}$$

Equation 01

$$\begin{aligned}\sigma^2{}_{l,t} = {} & 6 * 10^{-6^{(a)}} + 0.002^{(a)}\varepsilon^2{}_{b,t-1} + 0.057^{(a)}\varepsilon_{b,t-1}\varepsilon_{l,t-1} \\ & + 0.402^{(a)}\varepsilon^2{}_{l,t-1} + 0.0001^{(a)}\sigma^2{}_{b,t-1} \\ & + 0.018^{(a)}\sigma_{lb,t-1} + 0.734^{(a)}\sigma^2{}_{l,t-1}\end{aligned}$$

Equation 0

$$\begin{aligned}\sigma_{bl,t} = {} & -1.23 * 10^{-6^{(a)}} + 0.016^{(a)}\varepsilon^2{}_{b,t-1} + 0.215^{(a)}\varepsilon_{b,t-1}\varepsilon_{l,t-1} \\ & - 0.16^{(a)}\varepsilon^2{}_{l,t-1} + 0.01^{(a)}\sigma^2{}_{b,t-1} + 0.772^{(a)}\sigma_{bl,t-1} \\ & + 0.07^{(a)}\sigma^2{}_{l,t-1}\end{aligned}$$

Equation 0.3

Note: Superscript letter a, b and c represent 1%, 5% and 10% significant levels respectively.

In this section, the second part of the fourth hypothesis would be discussed via conditional variance equations. All coefficients in conditional variance equation are significant at the conventional level. That implies both Bitcoin and Litecoin volatilities are affected by "news" (shocks) and volatility generated by these two cryptocurrencies. The "news" information could be examined via coefficients of lag of squared residuals and cross-product of residuals. The "volatility" information could be examined via coefficients of lag of variance and covariance. In another word, there exist both short-run (ARCH effect) and long-run (GARCH effect) persistence from past shocks and volatilities for both Bitcoin and Litecoin. In addition, the volatility spill-over effects will be examined in both short and long run via examining the cross causality in the variance between Bitcoin and Litecoin volatility of returns. In order to examine the long run spill-over effect, the relationship between Bitcoin and Litecoin volatility need to be stable in the long run. Results indicate the volatility for Bitcoin is not stable in the long run since its root is 1.076 which is greater than 1. This implies given the conditions being provided, the variance of Bitcoin will eventually increase at an exponential rate of 1.076. For the equation of conditional volatility for Litecoin, the result suggests the root is 1.020 which is also greater than 1. Hence, it is not stable in the long run either. However, the value of this root is much less than 1.076. This implies the Litecoin volatility, in the long run, could be considered stable within the sampling error. The stability result for the conditional covariance equation suggests the covariance between Bitcoin and Litecoin is stable the long run. Note that the whole system is not stable in the long run. Such issue could be addressed by employing dynamic conditional correlation (DCC) model where the covariance of Bitcoin and Litecoin returns changes each time period. The analysis of DCC will be discussed in the next section for robustness check. In this section, the main focus is the short-run relationship between two markets and the spill-over effects. In the next chapter, variance breaks would be considered in the conditional variance equations in order to obtain stability of the whole system for analysis of cryptocurrency portfolio and the hedging effectiveness of such portfolio.

3.8.1.2.1. Own shocks and volatilities

The level of sensitivity to own news have large different for Bitcoin and Litecoin. Litecoin is nearly three times more sensitive to news 0.402>0.128. However, it could be seen that Bitcoin is also very sensitive to news (0.128). A positive shock in either Bitcoin or Litecoin market will lead to increase of their volatilities since the coefficients on the squared of residuals for both Bitcoin and Litecoin are positive. This might suggest that when comparing to Litecoin, Bitcoin being a market leader is more stable in reacting to shocks because more people would be supporting Bitcoin while less people would have the same faith on Litecoin as in Bitcoin.

Diagonal elements in variance covariance matrix represents own volatility dependency for Bitcoin and Litecoin. Coefficients on variables ${\sigma^2}_{b,t-1}$ and ${\sigma^2}_{l,t-1}$ on the first and second conditional variance equations show the sensitivity of own past volatility for Bitcoin and Litecoin respectively. Moreover, the half-life for both Bitcoin and Litecoin volatility could be calculated using the following equation where measure the persistence of the volatility:

$$Half\ life = \frac{\log(0.5)}{\log(\alpha_1 + \beta_1)}$$

Equation 0.1.1

Where α_1 and β_1 are coefficients on first lag of squared of standardized residual errors and first lag of variance. As mentioned before, the half-life measure the time taken for half of the influence of volatility to disappear. Results suggest half-life for Bitcoin and Litecoin are 10.8 and 2.3 respectively which implies it takes about 10 days and 2 days for half of the volatility effect to decay. Therefore, Bitcoin volatility is more persistent than Litecoin volatility. These values are much greater than coefficients on lag of squared residuals which might imply that Bitcoin and Litecoin are more influenced by fundamental factors such as demand and supply and technical factors. Bitcoin is shown to have higher volatility sensitivity (0.81) than Litecoin. But Litecoin should also be considered as high volatility sensitive (0.73).

3.8.1.2.2. Short-run shock interdependency

Cross shock effects are significant but in opposite directions for both Bitcoin and Litecoin at 1% significant level. Bitcoin conditional volatility is negatively (-0.18) affected by Litecoin past shock while Litecoin conditional volatility is positively affected by Bitcoin past shock. This implies shocks from Litecoin market are likely to cool off Bitcoin volatility. While Bitcoin volatility would enhance the Litecoin volatility in short run (0.06), but the impact would not be as large as its own shock since 0.06<0.40. The negative cross effect on Bitcoin might offset more Bitcoin's own news sensitivity effect if Bitcoin and Litecoin form a diversified portfolio.

3.8.1.2.3. Long-run volatility interdependency

The cross volatility in the past also has a significant impact on both Bitcoin and Litecoin. Both coefficients on $\sigma_{bl,t-1}$ for the first and second conditional variance equations are positive. In addition, results show cross volatility impacts are much weaker than their own volatility impacts. Results suggest Bitcoin and Litecoin should not be included in a portfolio if the aim is only to reduce the volatility instead of maintaining or increasing returns. Moreover, by transforming to VECH representation and calculate the roots of VEHC recursion, the dominant root 1.07942 is greater than 1. Hence the long-run covariance is not stable so that a portfolio of Bitcoin and Litecoin might not form a well-diversified portfolio.

3.8.2. Model B: VARX(2,1)-MGARCH(1,1)-Mean-DCC

For robustness check, another type of multivariate GARCH model is employed to see if regression coefficient estimates are coherent between these two types of estimations. A reason for choosing dynamic covariance correlation (DCC) model is provided above. In addition, it could estimate time-varying correlation which is useful in financial management such as asset allocation and risk assessment. The following Table 7 represents the results for an estimated model which will be discussed along with the results from previous BEKK model. Unlike BEKK which allows conditional covariance to be estimated. This DCC model considers off-diagonal elements of the variance-covariance matrix as zero. However, other useful results could be obtained from time-varying correlation.

Variable	Parameters	Coefficients	Standard Error	p-value
Mean Equation(lr_b)				
1. $lr_{b,t-1}$	φ_{11}	0.1937 [a]	0.0192	0.000
2. $lr_{b,t-2}$	φ_{12}	0.0213	0.0205	0.298
3. $lr_{l,t-1}$	τ_{11}	-0.0639 [a]	0.0104	0.000
4. $lr_{l,t-1}$	τ_{12}	0.0419 [a]	0.0080	0.000
5. Constant		-0.0014 [a]	0.0002	0.000
6. $w_{b,t-1}$	ϕ_{11}	0.0119	0.0117	0.310
7. $w_{l,t-1}$	ϕ_{12}	-1.096 [a]	0.2329	0.000
8. $lv_{b,t-1}$	γ_{11}	0.0017 [a]	0.0000	0.000
9. $lv_{l,t-1}$	γ_{12}	-0.0013 [a]	0.0000	0.000
10. $dh_{b,t-1}$	δ_{11}	0.0051	0.0060	0.390

11. $dh_{l,t-1}$	δ_{12}	0.0191[b]	0.0092	0.037
12. $\sigma^2_{b,t-1}$	λ_{11}	5.6050[a]	0.4052	0.000
13. $\sigma_{bl,t-1}$	λ_{12}	0.3657	0.2524	0.147
14. $\sigma^2_{l,t-1}$	λ_{13}	-0.0516	0.1136	0.650
Mean Equation(lr_l)				
15. $lr_{b,t-1}$	τ_{21}	0.6587[a]	0.0147	0.000
16. $lr_{b,t-2}$	τ_{22}	0.3001[a]	0.0182	0.000
17. $lr_{l,t-1}$	φ_{21}	-0.2960[a]	0.0194	0.000
18. $lr_{l,t-2}$	φ_{22}	-0.0594[a]	0.0208	0.004
19. Constant		-0.0095[a]	0.0002	0.000
20. $w_{b,t-1}$	ϕ_{21}	0.0004	0.0153	0.977
21. $w_{l,t-1}$	ϕ_{22}	0.571	0.3741	0.126
22. $lv_{b,t-1}$	γ_{21}	-0.0034[a]	0.0000	0.000
23. $lv_{l,t-1}$	γ_{22}	0.0014[a]	0.0000	0.000
24. $dh_{b,t-1}$	δ_{21}	0.0095	0.0070	0.169
25. $dh_{l,t-1}$	δ_{22}	0.0036	0.0095	0.707
26. $\sigma^2_{b,t-1}$	λ_{21}	8.7582[a]	0.4411	0.000
27. $\sigma_{lb,t-1}$	λ_{22}	-1.1807[a]	0.4163	0.005
28. $\sigma^2_{l,t-1}$	λ_{23}	0.5610[a]	0.2108	0.008
Conditional variance-covariance Model				
29. C(1)		0.00002[a]	0.0000	0.000
30. C(2)		0.00002[a]	0.0000	0.000
31. A(1)		0.2160[a]	0.0072	0.000
32. A(2)		0.2705[a]	0.0052	0.000
33. B(1)		0.7626[a]	0.0037	0.000
34. B(2)		0.7848[a]	0.0024	0.000
35. DCC(A)		0.1851[a]	0.0013	0.000
36. DCC(B)		0.8102[a]	0.0013	0.000

Table 7: Estimated results for DCC model. Note that superscript letter a, b and c represent 1%, 5% and 10% significant levels respectively.

3.8.2.1. Conditional mean equation

In this second estimated model, results for the lag of return in both Bitcoin and Litecoin are highly consistence with the results presented in Model A. All lag returns are significant at 1% significant level except for second lag of Bitcoin return which was not significant in predicting Bitcoin current return. The signs for the lag returns coefficients are the same, and the magnitudes of coefficients are very close. Both constant terms are significant in both conditional mean equations. However, not many exogenous variables are significant compare to results from model A. In this model, Wikipedia view variables are not significant in either cryptocurrency even at 10% significant level. This result support Model A that Wikipedia views of Bitcoin and Litecoin could not be used to predict Bitcoin return and Wikipedia view of

Bitcoin does not help to predict Litecoin current return neither. Similar to Model A, there exist negative cross effects of transaction volumes in both Bitcoin and Litecoin. In Model B, both cross effects in transaction volumes are significant at 5% level. The impact of Bitcoin transaction volume on Litecoin return is greater than the impact of Litecoin transaction volume on Bitcoin which is also consistent with results in Model A. For growth of hashrate, Litecoin hashrate is shown to have significant positive impact on Bitcoin return at 5% significant level. An increase of growth of hashrate for Litecoin in 1% will lead to increase of Bitcoin current return by 0.02%. But other hashrate variables were not significant. This could be explained that as an increase of hashrate is equivalent to an increase of a number of miners. The incentive for miners is to make a profit via mining Bitcoin (or receiving a small amount of transaction fee). Therefore, it implies the raise of Litecoin price. The raise of Litecoin price might cause people to sell Litecoin at a high price and purchase Bitcoin as a safe cryptocurrency. Results of variance and covariance in conditional mean equation indicate Bitcoin return is not affected by the covariance of Bitcoin and Litecoin. Meanwhile, own volatilities from Bitcoin and Litecoin were significant in predicting both Bitcoin and Litecoin current returns.

In summary, results for Model A and Model B are mostly coherent in terms of magnitude, sign and significant level of estimated coefficients. Except for the growth of hashrate for Litecoin and the conditional variance and covariance of Bitcoin and Litecoin in both conditional mean equations. In Model A, the growth of hashrate of Litecoin was significant predicating its own current return at 10% significant level but insignificant in predicting Bitcoin current return. However, the results suggest the opposite for Model B where the growth of hashrate for Litecoin was significant at 5% level in predicting Bitcoin current return. In terms of variance-covariance in conditional mean equation. The covariance of Bitcoin and Litecoin returns become insignificant in predicting the Bitcoin current return. Therefore, Model B concludes that the first and second hypotheses are fully confirmed where neither of the cryptocurrency markets are efficient. In addition, there exists bi-directional causality relationship between Bitcoin and Litecoin returns. The third hypothesis is partly confirmed since not all variables are significant, which gives the same conclusion as for Model A. Moreover, volatility transmission could only be found in the conditional mean equation for Litecoin return.

3.8.2.2. Conditional variance equation

Estimated univariate GARCH

$$\sigma_{b,t-1} = 0.00002^{(a)} + 0.216^{(a)}\varepsilon^2{}_{b,t-1} + 0.763^{(a)}\sigma^2{}_{b,t-1}$$ *Equation 3.8.2.1*

$$\sigma_{l,t-1} = 0.00002^{(a)} + 0.27^{(a)}\varepsilon^2{}_{b,t-1} + 0.785^{(a)}\sigma^2{}_{b,t-1}$$ *Equation 3.8.2.2*

Estimated dynamic conditional covariance

$$Q_t = (1 - 0.185 - 0.81)^{(a)}\bar{Q} + 0.185^{(a)}z_{t-1}z'_{t-1} + 0.81^{(a)}Q_{t-1}$$ *Equation 3.8.2.3*

Where z_t represents the standardized residuals $z_t = \frac{\epsilon_t}{\sigma_t}$

Estimated dynamic conditional correlation

$$p_{bl,t} = \frac{q_{bl,t}}{\sqrt{q_{bb,t}q_{ll,t}}} = \frac{0.005\overline{q_{bl}} + 0.185z_{t-1}z'_{t-1} + 0.81q_{bl,t-1}}{\sqrt{\{0.005\overline{q_{bb}} + 0.185z_{t-1}z'_{t-1} + 0.81q_{bb,t-1}\}\{0.005\overline{q_{ll}} + 0.185z_{t-1}z'_{t-1} + 0.81q_{ll,t-1}\}}}$$ *Equation 3.8.2.4*

Note: Superscript letter a represents coefficients are significant at 1% level.

Both ARCH and GARCH terms suggest there exist short-run and long-run persistence. Conditional volatilities for Bitcoin and Litecoin are affected by their own shocks and volatilities at 1% significant level. Moreover, their conditional volatilities are more sensitive to their own past volatilities rather than past news since 0.763>0.216 and 0.785>0.27. The sum of ARCH (0.185) and GARCH (0.810) coefficients is less than unity which supports the presence of dynamic correlations in these two cryptocurrency markets and also implies the correlation dynamic is mean reverting. To further examine the dynamic conditional correlation, a graph is plotted, which shows dynamic conditional correlation coefficient has relatively high value on average. The correlation varied over the sample period from a low of -0.6 to a high value of close to 1. But the mean would always be reverted to a level that closes to 0.55. The average value of dynamic conditional correlation indicates Bitcoin and Litecoin provide very limited diversification benefits for portfolio investors.

3.8.3. Restricted Model

Restricted models for BEKK and DCC model have been estimated where Wikipedia view and hashrate variables are excluded in the conditional mean equation. Tables 8 and 9 from the appendix, show the results from restricted models support the results for the full model where the sign for these variables remain the same and there only exist slight changes in the magnitude of coefficients. In addition, the diagnostic test for standardized residuals also support the previous results. By testing the null hypothesis of Wikipedia view and growth of hashrate being zero. The F-test statistics for restricted BEKK and DCC models are F(8,*)=12.50 and F(8,*)=12.25 respectively which reject the null hypothesis at 1% significant level. Results indicate coefficients on both Wikipedia view and growth of hashrate are jointly significant.

3.9. Discussion and Conclusion

3.9.1. Comparison with previous studies

In line with the previous study from Gandal and Halaburda (2014) and Osterrieder(2017), many evidence of this study suggests Bitcoin acts as a market leader while Litecoin is a follower of Bitcoin. However, the reason for Bitcoin to have a much larger impact on Litecoin might mainly due to the size of its capitalization. This is one of the limitations of this study. In line with the majority of previous studies that Bitcoin acts as an asset rather than currency (Baur(2015), Yermack (2013), Bouiyour and Selmi (2014), Florian (2014)). In addition to the previous studies, Litecoin is also found to have asset characteristics rather than currency.

Against to previous studies include Florian (2014), Kristoufek (2013), Nathnalie and Malin (2014) who found search traffic has a significant effect on the price of Bitcoin. This study found lack of evidence supporting the same finding. The search traffic is not found to be significant is further supported by evidence from Litecoin.

In line with Bouriyour and Selmi (2014), Gandal and Halaburda (2014), Chu and Nadarajah (2015), Nathnalie and Malin (2014), Balcilar et al., (2016), and Kristoufek (2015) where transaction volume has a negative significant impact on cryptocurrencies. This variable is further supported to be a significant factor in predicting cryptocurrency price because there exist negative cross-effect and Litecoin transaction volume also has a negative impact on its own return.

Kristoufek (2015) was the first to consider the effect of hashrate on Bitcoin. In this study, the growth rate of hashrate is being examined where results suggest growth of hashrate of Bitcoin does not have a significant impact on Bitcoin return. However, it has a significant positive effect on for Litecoin which is in line with finding from Kristoufek (2015).

In line with previous studies including Bouri et al, (2016), Qu (2017), Nathnalie and Malin (2014) who also found a significant correlation between volatility and return for Bitcoin. Nathnalie and Malin (2014) found volatility have a significant impact on Bitcoin return. However, this study found positive correlation between volatility and return for Bitcoin. This finding is further supported from the evidence of Litecoin volatility and return which is also positively correlated suggest an increase of risk would lead to higher rate of expected return. Against to other studies include Balcilar et al., (2015) and Parlstrand and Ryden (2015) who found there is no correlation between volatility and return for Bitcoin.

3.9.2. Conclusion and future work

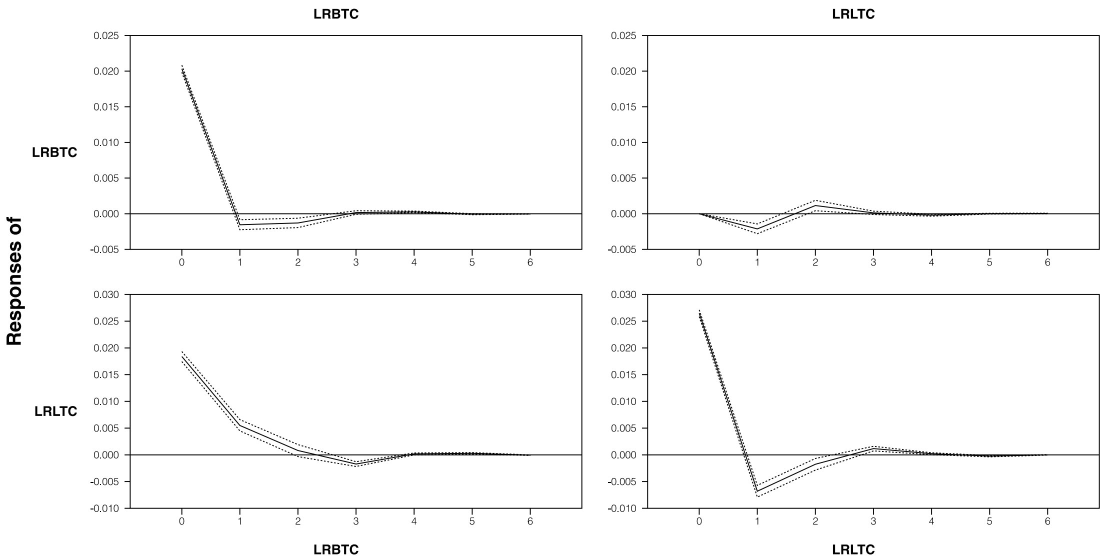
This is the first study that examines the dynamic relationship of two cryptocurrencies, Bitcoin and Litecoin by considering volatility transmission between these two cryptocurrencies and how factors of one cryptocurrency affect the other cryptocurrency. Results suggest transaction volume and growth rate of hashrates of one cryptocurrency have different degrees of impacts between Bitcoin and Litecoin.

Litecoin, being a follower of Bitcoin in cryptocurrency market, moves in the same direction as Bitcoin on average. This implies a diversified portfolio could be constructed. Moreover, diversification is not only about correlation. Parts of the findings suggest Litecoin exhibit some new feature when compare to Bitcoin which brings positive impact on Litecoin return. This implies people like holding cryptocurrency with better features. Bitcoin being the first cryptocurrency might only have the fundamental feature. Different features of Litecoin as cryptocurrency might be able to reduce another type of risks. Therefore, a diversified portfolio containing Bitcoin and Litecoin could be constructed in order to reduce the level of risk. Such implication is useful for an investor who wants to include cryptocurrency in their portfolio but is concerned about the risk.

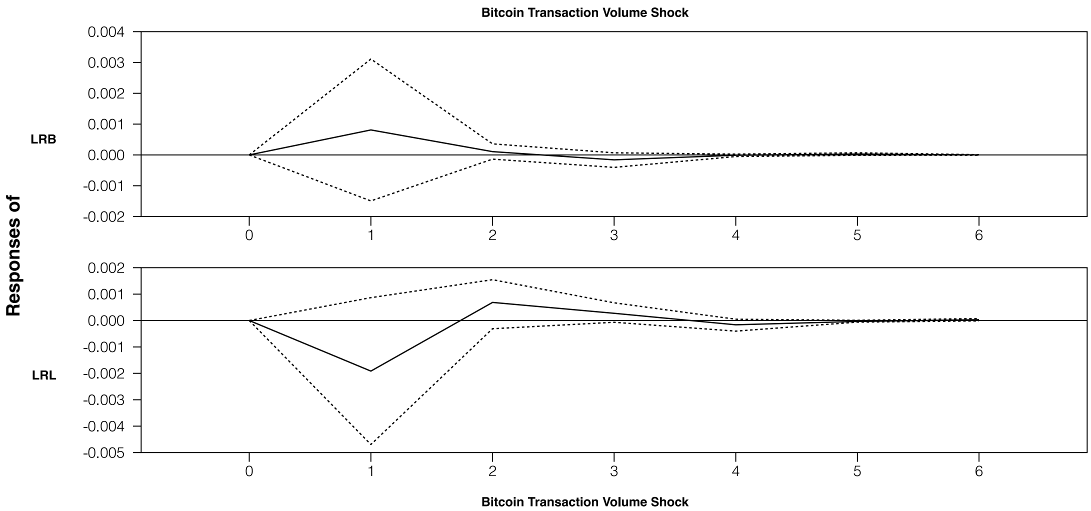
In the next chapter, a diversified portfolio of Bitcoin and Litecoin would be constructed using dynamic conditional correlation model where the covariance changes from period to period. Weights of each cryptocurrency would be calculated in order to obtain minimum risk for a certain level of return. After constructing a diversified portfolio, such portfolio could be used to examine whether it consists of financial capabilities such as hedging capability against some commodities, currencies, stocks and bonds.

One of the limitation of this chapter is that the covariance between Bitcoin and Litecoin volatility is not stable in the long run when using BEKK model. This problem could be addressed by considering structural break and consider different sub-sample periods. The same methodology could be applied to more than two cryptocurrencies and examine the dynamic relationship among them.

3.10. APPENDEIX

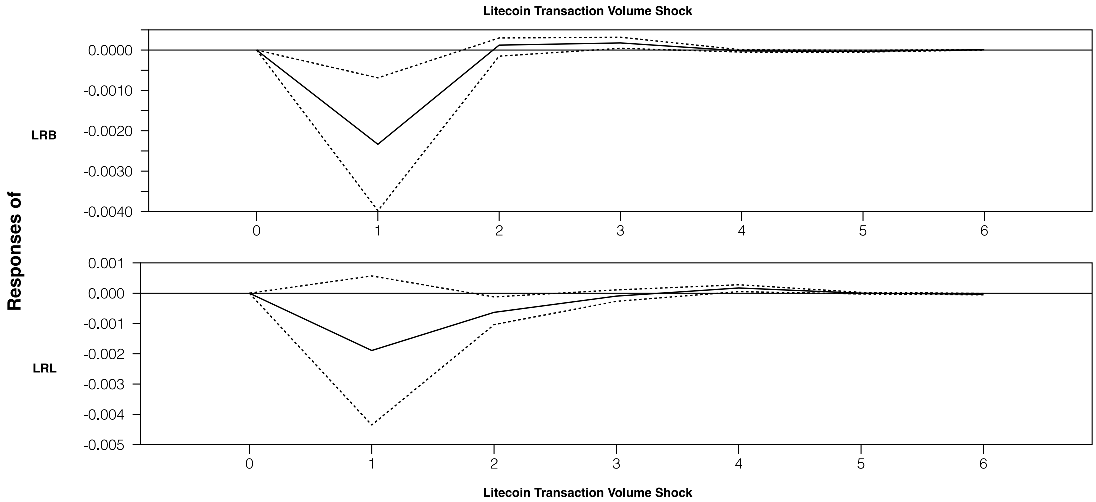


Graph 1: Impulse response of Log of Bitcoin (Litecoin) return on Bitcoin and Litecoin shocks. A unit shock on Bitcoin and Litecoin returns will lead to negative impacts on their own returns in the following period. A unit shock on Litecoin return will lead to negative impact on Bitcoin return. A unit shock of Bitcoin return will lead to positive impact on Litecoin return where the effect gradually decrease to zero in the second period and becomes negative in the third period. Detail description could be found in the end of section 3.8.1.1.1.



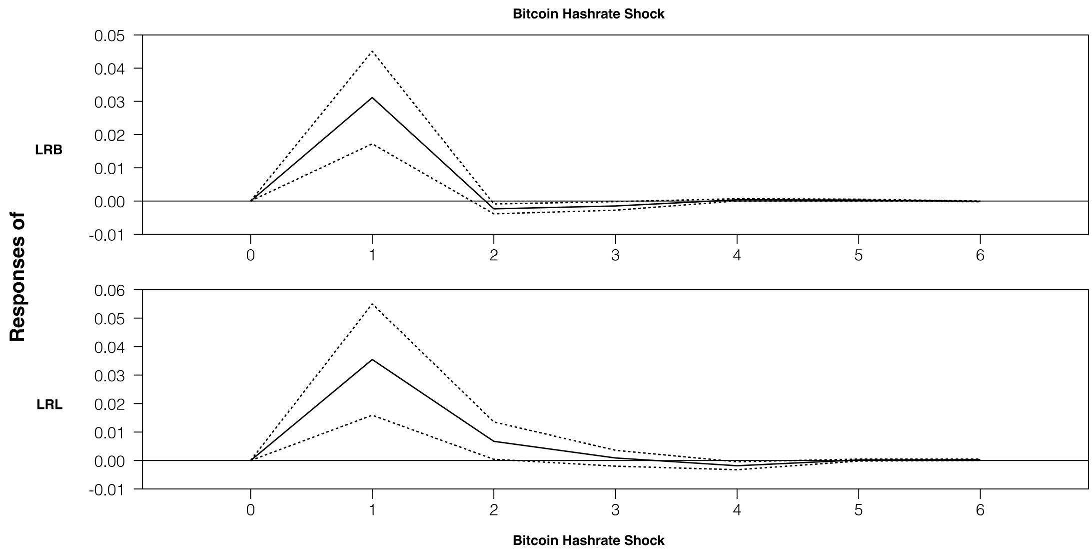
Response to Bitcoin Transaction Volume Shock

Graph 2: Response of Bitcoin and Litecoin returns on Bitcoin transaction shock. A unit shock of Bitcoin transaction volume will lead to positive and negative impact on Bitcoin and Litecoin price returns respectively. The impact on Litecoin return will become positive in the second period and gradually decrease to zero in the following periods. Detail description could be found in section 3.8.1.1.2.



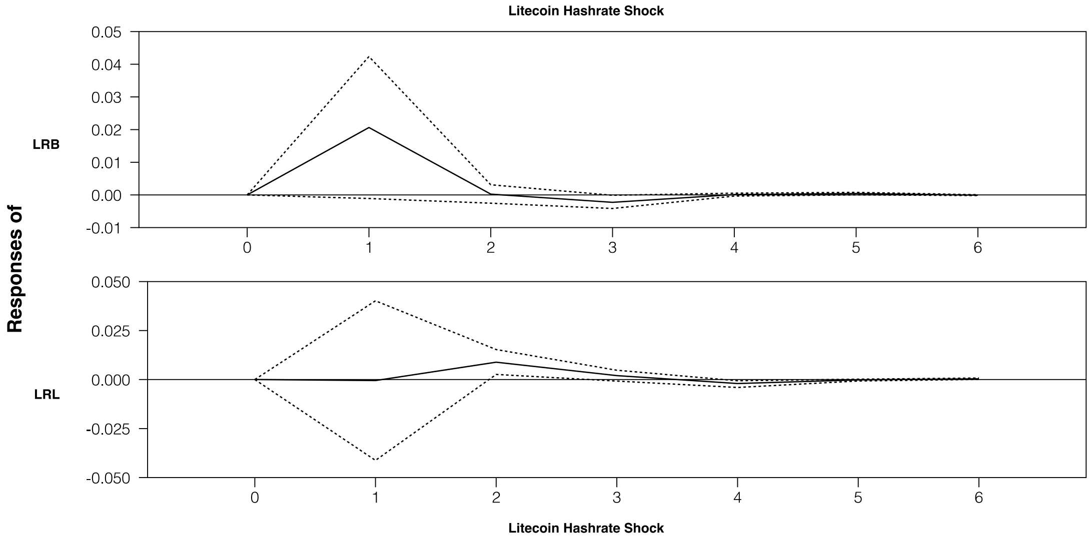
Response to Litecoin Transaction Volume Shock

Graph 3: Response of Bitcoin and Litecoin returns on Litecoin transaction shock. A unit shock of Litecoin transaction volume will lead to negative shock on both Bitcoin and Litecoin price returns in the first period.



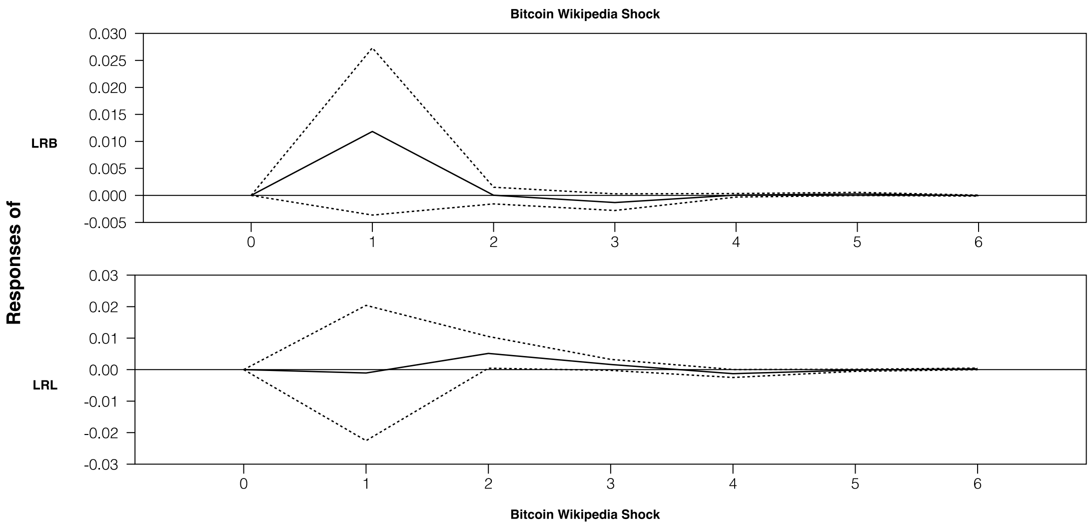
Response to Bitcoin Hashrate Shock

Graph 4: Response of Bitcoin and Litecoin returns on Bitcoin hashrate shock. A unit shock of Bitcoin hashrate will lead to positive impacts on both Bitcoin and Litecoin price returns in the first period and the effects gradually decrease to zero in the following periods. Detail description could be found in section 3.8.1.1.2.



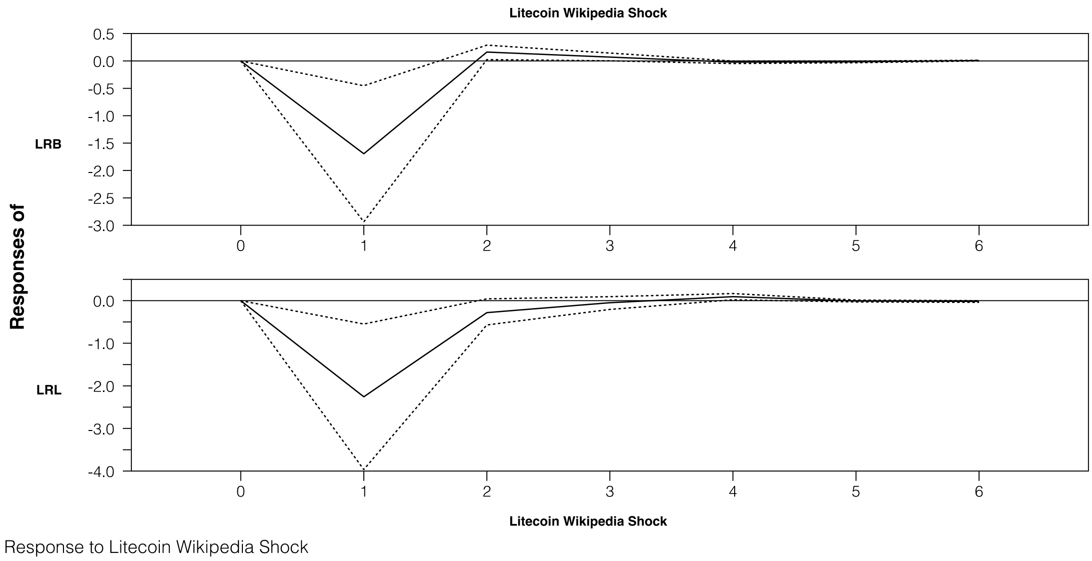
Response to Litecoin Hashrate Shock

Graph 5: Response of Bitcoin and Litecoin returns on Litecoin Hashrate shock. A unit shock of Litecoin hashrate will lead to positive impact on Bitcoin price return in the first period which is decreased to almost zero in the second period. The effect becomes negative in the third period. The same unit shock has positive effect on Litecoin price return on the second period and gradually decrease to zero in the following periods.



Response to Bitcoin Wikipedia Shock

Graph 6: Response of Bitcoin and Litecoin returns on Bitcoin wikipedia shock. A unit shock of Bitcoin Wikipedia view will lead to positive and negative effects for Bitcoin and Litecoin price return in the following periods respectively. Detail description could be found in section 3.8.1.1.2.



Graph 7: Response of Bitcoin and Litecoin returns on Litecoin Wikipedia shock. A unit shock of Litecoin Wikipedia shock will lead to negative effect on both Bitcoin and Litecoin price return in the following period but the effects decrease to almost zero in the second period. Detail description could be found in section 3.8.1.1.2.

Variable	Coeff	Std Error	P-value
Mean Model(LRB)			
1. LRB{1}	0.1473	0.0208	0.000
2. LRB{2}	0.0134	0.0252	0.596
3. LRL{1}	-0.0608	0.0113	0.000
4. LRL{2}	0.0267	0.0143	0.062
5. Constant	-0.0055	0.0003	0.000
6. LVB{1}	0.0004	0.00004	0.000
7. LVL{1}	-0.0009	0.00004	0.000
8. HHS(1,1)	4.9448	0.4190	0.000
9. HHS(2,1)	0.4225	0.2800	0.131
10. HHS(2,2)	-0.1771	0.1345	0.188
Mean Model(LRL)			
11. LRB{1}	0.6176	0.0154	0.000
12. LRB{2}	0.2995	0.0204	0.000
13. LRL{1}	-0.3183	0.0206	0.000
14. LRL{2}	-0.0733	0.0242	0.002
15. Constant	-0.0010	0.0002	0.000
16. LVB{1}	-0.0035	0.00003	0.000
17. LVL{1}	0.0024	0.00003	0.000
18. HHS(1,1)	12.660	0.5057	0.000
19. HHS(2,1)	-4.533	0.4322	0.000
20. HHS(2,2)	0.837	0.2218	0.000
21. C(1,1)	0.00419	0.00006	0.000

22. C(2,1)	-0.00047	0.0002	0.042
23. C(2,2)	0.0025	0.0002	0.000
24. A(1,1)	0.3508	0.0066	0.000
25. A(1,2)	-0.2623	0.0137	0.000
26. A(2,1)	0.04462	0.0043	0.000
27. A(2,2)	0.63207	0.0063	0.000
28. B(1,1)	0.90008	0.0015	0.000
29. B(1,2)	0.0864	0.0031	0.000
30. B(2,1)	0.0117	0.0013	0.000
31. B(2,2)	0.8554	0.0017	0.000

Table 8: Restricted VARX-GARCH-M-BEKK model

Variable	Coeff	Std Error	P-value
Mean Model(LRB)			
1. LRB{1}	0.1831	0.0189	0.000
2. LRB{2}	0.0234	0.0204	0.251
3. LRL{1}	-0.0558	0.0104	0.000
4. LRL{2}	0.0409	0.0085	0.000
5. Constant	-0.0039	0.0003	0.000
6. LVB{1}	0.0015	0.00004	0.000
7. LVL{1}	-0.0016	0.00004	0.000
8. HHS(1,1)	7.4046	0.3883	0.000
9. HHS(2,1)	-0.5897	0.2423	0.015
10. HHS(2,2)	-0.1771	0.1153	0.124
Mean Model(LRL)			
11. LRB{1}	0.6615	0.0146	0.000
12. LRB{2}	0.3039	0.0179	0.000
13. LRL{1}	-0.2989	0.0194	0.000
14. LRL{2}	-0.0614	0.0202	0.002
15. Constant	-0.0120	0.0002	0.000
16. LVB{1}	-0.0032	0.00004	0.000
17. LVL{1}	0.0017	0.00003	0.000
18. HHS(1,1)	8.6046	0.4230	0.000
19. HHS(2,1)	-1.1129	0.3806	0.003
20. HHS(2,2)	0.7940	0.1962	0.000
21. C(1)	0.00003	0.0000008	0.000
22. C(2)	0.00002	0.0000009	0.000
23. A(1)	0.2123	0.0069	0.000
24. A(2)	0.2723	0.0052	0.000
25. B(1)	0.7639	0.0037	0.000
26. B(2)	0.7846	0.0024	0.000
27. DCC(A)	0.1883	0.0013	0.000
28. DCC(B)	0.8070	0.0013	0.000

Table 9: Restricted VARX-GARCH-M-DCC model

Chapter 4

4.1. Introduction

Bitcoin market has grown rapidly in the past few years in terms of transaction volume and its capital value. Being the first decentralized cryptocurrency, Bitcoin has continuously surpassed its own trading value in the past one year. Its value has increased more than 5 times than the peak value of 1000 US dollars in 2014. Although its price has increased dramatically, its volatility has been more stable in the last three years when compared to the period before 2014. In the meantime, many other cryptocurrencies also experienced significant growth in their values in the past few years. Some of them even have greater growth rate than Bitcoin, for instance, Ethererum has experienced 3500% of growth rate within one year since the beginning of 2017. However, the majority of them act more like tokens which are being used in their platform for specific purposes, whereas Bitcoin acts more like currency in terms of usage where they could be used to purchase goods or service just like fiat currency. The characteristics of these cryptocurrencies have been discussed in details in the third chapter. For the same reason that was mentioned in the third chapter. Litecoin will be used to form a portfolio with Bitcoin as they are more alike but at the same time, Litecoin has different features to Bitcoin, for instance, it is more efficient than Bitcoin in terms of transaction fee, confirmation waiting time and mining cost. The Litecoin's value did not grow as quick as other popular cryptocurrencies such as Bitcoin and Ethereum. But it also has grown significantly compared to traditional assets such as the bond, equity and real estate. The growth in all these cryptocurrencies has raised the risks of cryptocurrency markets. Therefore, some investors might find the need to form a cryptocurrency portfolio that has some financial capability. In the previous chapter, the dynamic relationship between Bitcoin and Litecoin have been examined, and significant relationship such as spillover effect has been observed. Further to the previous chapter, this chapter is going to examine whether the relationship between Bitcoin and Litecoin could lead to financial benefits for investors. More specifically, the portfolio of Bitcoin and Litecoin will be used to examine the existence of financial capabilities such as asset diversifying and hedging for such a portfolio along with the examination of other traditional assets including commodities, equities and currencies.

As defined by Baur and Lucey (2010), an asset is said to be a diversifier if it is positively but not perfectly correlated with another asset or portfolio on average. An asset is said to be a hedge if it is uncorrelated or negatively correlated with another asset or portfolio on average. Although there are a few studies, have been examining the hedging capability of Bitcoin against other traditional assets. But the findings from these studies are mixed. Moreover, none of them has considered the hedging capability of a portfolio that only contains cryptocurrencies Details of the findings from previous studies will be discussed in detail in the literature review section below. Therefore, this chapter will employ dynamic conditional correlation model to estimate the correlation coefficients between cryptocurrencies and traditional assets because such model allows to examine the time-varying correlation process and it often provides better estimation than simple multivariate GARCH model. Billio and Caporin (2009) suggest dynamic conditional correlation model is useful for examining asset allocation and portfolio risk evaluation. In this chapter, a vector autoregressive model along with bivariate dynamic conditional correlation model will be employed in which both Bitcoin and Litecoin returns are regressed on commodity, equity and currency return respectively.

Being a new type of assets, cryptocurrencies have advanced and different features than some traditional assets which might lead to low correlation or no correlation with traditional assets. In addition, the capitalization for cryptocurrency market is growing at a rapid rate. Such growth is also an important feature in an era of globalization, as liquidity is the main factor for an investor to consider in their investment. Although Bitcoin market has nearly 100 billion US dollar capitalization. It is safe to assume that Bitcoin or Litecoin markets have little impact on traditional financial markets such as commodity, equity and currency markets. In the end, portfolio hedging possibilities and optimum weights would be discussed to see if such portfolio is effective on hedging against traditional assets.

4.2. Literature review

Following an increase of interest rate by the US Federal Reserve, the value of US dollar has strengthened to a higher level leading a growth of financial markets such as stock market where Dow Jones Industrial Average Index has risen to a new record. This growth also leads to an increase in risks for the financial system. For foreign individual investors, there is potential need to hedge against US dollar in case an unlikely event happens; US dollar starts falling. Moreover, some countries such as Zimbabwe has been experiencing hyperinflation since 2003 until the country abandoned Zimbabwean dollar and adopted multiple types of fiat currencies including US dollar. Zimbabwe citizens could potentially protect their US dollar from falling through holding another negatively correlated currency in order to maintain the value of their currency assets. In order to answer whether currency risk is worthy of hedging. Santis and Gerard (1998) show currency risk ha a significant economic impact, and it involves a large fraction of total risk for foreign investment. Andersen et al. (2007) show the exchange rate market is more volatile when compared to bond markets in the US, UK and German.

4.2.1. Role of gold

Bitcoin has been known as digital gold as it shares many similar features as gold. As a metal commodity, gold has often been considered as a safe haven or hedge against other financial assets and inflation. There is no theoretical model explaining why gold could be used as a safe haven. One explanation could be that gold was the first form of globally recognized money and it was used to hedge against inflation due to scarcity (Baur and Lucey, 2010). Capie et al. (2005) are the first to discuss the hedging property of gold against fiat currency. However, Capie et al. (2005) do not distinguish the difference between the hedge and safe haven. Whereas Baur and Lucey (2010) define hedging of one asset is non-positively correlated with another asset (or portfolio) on average. The definitions from Baur and Lucey (2010) are employed in the later studies. They distinguish the difference between the hedge and safe haven on the period of time that an asset is being examined. A hedge of an asset could display a positive correlation with another asset if the period of time is under market stress but becomes negatively correlated for the rests of the normal time. They define safe haven as an asset that is non-positively correlated with another asset in the times where the market is under turmoil. As a safe haven, an asset could exhibit any relationship with another asset during the normal times or under bullish market conditions. At last, they define a diversified asset is non-negatively correlated with another asset on average. The purposes of hedge, safe haven and diversified assets varied under different circumstances. Both hedge and diversified assets do not help to reduce losses when the market is experiencing an extreme down time.

A hedge asset aims to minimize the risk in a portfolio while avoiding any losses on average. Whereas a diversified asset aims to reduce risk to a lower level while maintaining a reasonable return level on average. Baur and McDermott (2010) define hedge, safe haven and diversifier in more specific definitions. A strong (weak) hedge is an asset that is negatively correlated (uncorrelated) with another asset on average. A strong (weak) safe haven is an asset that is negatively correlated (uncorrelated) with another asset in extreme adverse market conditions. A strong (weak) diversifier is an asset that is uncorrelated (positively correlated) with another asset on average.

Baur and Lucey (2010) examine whether gold behaves hedge or safe haven properties for both stocks and bonds markets for the US, UK and German. Daily data are used between 30/11/1995 and 30/11/2005. Return of gold is regressed on both stock and bond returns dependent variables as well as two dummy variables to capture movement when the market is falling in extreme conditions. The following ordinary least square regression is regressed:

$$r_{gold,t} = a + b_1 r_{stock,t} + b_2 r_{stock,t(q)} + c_1 r_{bond,t} + c_2 r_{bond,t(q)} + e_t \qquad \text{Equation 4.2.1.1}$$

where $r_{gold,t}$ $r_{stock,t}$ and $r_{bond,t}$ represent the gold, stock and bond returns at time t restively. Both $r_{stock,t(q)}$ and $r_{stock,t(q)}$ are able to consider asymmetries shocks which focus on negative shocks in this case when stock or bond returns are at q% quartiles. These two dummy variables take the value of zero if the return is greater than q% quantile. They assumed both contemporaneous and lagged of stock and bond prices affect gold price. Followed by the approach by Capie et al., (2005), Baur and Lucey (2010) employ GARCH process to estimate the dynamic regression because these traditional assets have different impacts on the gold return when they are in lagged terms rather than contemporaneous terms. Generalized autoregressive heteroskedasticity model, GARCH (1,1), is being used. The results suggest gold could be used as a safe haven for stock markets in all three countries. Empirical evidence also suggests gold could be used as a hedge against stock markets for both US and UK. Gold does not exhibit hedging property for the stock market in German. There is lack of evidence suggesting gold behaves as a hedge or safe haven for bond markets in both US and UK. Baur and McDermott (2010) examine whether gold acts as a safe haven in the global financial system in 13 developed and developing countries between 02/03/1979 and 02/03/2009. Both daily and weekly data are used. As in Baur and Lucey (2010), GARCH (1,1) model is used but only for stock markets in these 13 countries. In the mean equation, explanatory variables only include three dummy variables for capturing extreme movement in stock markets which equal to one if the market exceeds 10%, 5% or 1% quantile of the return distribution. Strong evidence from using daily data suggests gold acts as a strong and weak safe haven for most of the stock markets in developed countries and emerging countries respectively.

After that, many studies examine the properties of gold in different markets for a different period of times. Apart from testing the relationships with stock and bond markets in different countries. Gold is also used to test whether it acts as a hedge against commodity, exchange rate and inflation. However, results are not consistent all the time.

Joy (2011) examines whether gold acts a hedge against US dollar using weekly data between 10/01/1986 and 29/08/2008. Dataset consists 16 US dollar paring exchange rates. Dynamic conditional correlation model is employed with these 16 exchange rates which are being examined simultaneously. Results suggest gold acts as a hedge against US dollar for the examined period of time. Correlation between gold price and US dollar exchange rates become more negatively correlated when it gets closer to 2008 and reaching the strongest negative relationship with US dollar exchange rates in 2008. Ciner et al., (2012) employ dynamic conditional correlation model to examine properties of financial assets among each other. Daily data between January of 1990 and June of 2010 is collected for stock, bond, currency, gold and oil markets in both US and UK. Both US dollar and UK sterling indices are used to represent currency variables. Results show gold could be used as a hedge against dollar and sterling exchange rates fluctuations on average. In addition, gold shows safe haven property when both dollar and sterling experience significant fall in exchange rate markets. Iqbal (2016) adopts the framework similar to Baur and Lucey (2010) and employ EGARCH(1,1) model for testing whether gold acts as a hedge against inflation, stocks and exchange rates in India, Pakistan and US. Using both daily and monthly data between 1990 and 2013. Results show gold acts as a hedge against currencies for both India and Pakistan for both daily and monthly data.

4.2.2. Bitcoin hedging

Ennis (2013) is the first to examine the financial ability of Bitcoin. He adopts the methodology from Baur and Lucey (2010) and Ciner et al. (2010, revised 2012) to test whether Bitcoin acts as a hedge, safe haven against other financial assets between 19 July 2010 and 21 June 2013 with daily data. These assets include stocks, bond and currencies for both US and European markets. Stocks are represented by 3 stock indices from the US and 2 stock indices from Europe. Both US dollar index and euro index are used to represent currency variables. The first GARCH(1,1) model is used to examine whether Bitcoin is a hedge or diversifier against stocks, bonds and currencies which is shown as follow:

$$r_{bitcoin,t} = constant + b_1 r_{stock,t} + b_2 r_{bond,t} + b_3 r_{currency,t} + e_t$$ Equation 4.2.2.1

where $r_{bitcoin,t}, r_{stock,t}, r_{bond,t}$ and $r_{currency,t}$ are returns for bitcoin, stocks, bonds and currencies. The model is regressed for each stock index for both US and European markets. Therefore, there are three versions of model one. The second GARCH model includes two quintiles variables that are used to account for extreme movement from stocks, bonds and currencies in the mean equation which are denoted as $r_{stock,t(q)}, r_{bond,t(q)}$ and $r_{currency,t(q)}$. The second model is used to test whether Bitcoin is a safe haven against these financial assets when the market experience extreme down time.

For the first model, Bitcoin neither act as a hedge nor diversifier against stocks, bonds and currency in the US market at 5% significant level. However, Bitcoin acts as diversifier against bonds in the European market at 5% significant level. For the second model, Bitcoin acts as a safe haven against Dow Jones Industrial Average Index at 5% significant level. Bitcoins acts as a safe haven against euros at 5% significant level. Results for Bitcoin acts as a safe haven is not consistent for stock and bond market in Europe.

Briere et al. (2013) examine whether Bitcoin acts as a diversifier in a portfolio along with other traditional assets and alternative investments. Correlations between Bitcoin and other assets including worldwide stock, bonds, currencies, gold, oil and real estate price are examined using weekly data between 23 July 2010 and 12 July 2013. Results suggest Bitcoin has low correlation with these assets and could be used as a diversifier. The above two studies are the first to examine the financial ability of Bitcoin.

However, the main drawback for these studies is that they did not include the period from July of 2013 until 2014. Bitcoin price has increased to 1000 US dollar from less than 100 US dollar within a few month times. Later on, other studies include this period when examining the Bitcoin ability on hedging and different methodologies are also employed in these studies. With consideration for the period of extreme movement in Bitcoin price, there are not many studies examining the hedging capability of Bitcoin. Only three studies were found to have hedging capability. Another two studies found hedging property of Bitcoin varies over time.

Dyhrberg (2015a) uses two GARCH models to examine the property of Bitcoin by using daily data between 19 July 2010 and 22 May 2015. The first model regress bitcoin returns on its own lagged return and some explanatory variables in the mean equation and variance equation as follow:

$$\begin{aligned} r_{bitcoin,t} = \beta_0 + \beta_1 r_{bitcoin,t-1} + \beta_1 r_{bitcoin,t-2} + \beta_2 Fed_{t-1} \\ + \beta_3 USDEUR_{t-1} + \beta_4 USDGBP_{t-1} + \beta_5 FTSE_{t-1} \\ + \beta_6 Goldf_{t-1} + \beta_7 Goldc_{t-1} + \varepsilon_t \end{aligned}$$

Equation 4.2.2.2

$$\begin{aligned} \sigma_t^2 = \exp(\lambda_0 + \lambda_1 Fed_{t-1} + \lambda_2 USDEUR_{t-1} + \lambda_3 USDGBP_{t-1} \\ + \lambda_4 FTSE_{t-1} + \lambda_5 Goldf_{t-1} + \lambda_6 Goldc_{t-1}) \\ + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \end{aligned}$$

Equation 4.2.2.3

where Fed, USDEUR, USDGBP, FTSE, Goldf and Goldc represent federal funds rate, exchange rates for USD/EUR and USD/GBP, financial times stock exchange index, CMX gold futures and gold bullion rate respectively.

The second exponential GARCH model considers the asymmetric effect so that it could be used to examine how Bitcoin reacts to the good and bad news. It has the same mean equation as above, but different variance equation is shown as below:

$$\ln(\sigma_t^2) = \lambda_0 + \lambda_1 Fed_{t-1} + \lambda_2 USDEUR_{t-1} + \lambda_3 USDGBP_{t-1} + \lambda_4 FTSE_{t-1} + \lambda_5 Goldf_{t-1} + \lambda_6 Goldc_{t-1} + \alpha\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \gamma\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right) + \delta\ln(\sigma_{t-1}^2)$$ *Equation 4.2.2.4*

Results from both models suggest Bitcoin could be used to hedge against US dollar only. Moreover, it was found there is no asymmetric effect on the volatility of bitcoin return.

By using the same dataset, Dyhrberg (2015b) adopts the methodology from Baur and Lucey (2010) and examines the hedging ability of bitcoin against FTSE index. Both contemporaneous and lagged term of FTSE is included in the mean equation in GARCH model. Results suggest bitcoin can hedge against stocks in FTSE index. A threshold GARCH is also employed to capture the dynamic relationship between bitcoin return and exchange rates including USD/GBP and USD/EUR. Contemporaneous and lagged terms of exchange rates are included in both of the mean equations. Results suggest bitcoin could hedge against US dollar in the short term.

Bouri et al., (2017a) examine whether Bitcoin can hedge global uncertainty by using uncertainty index (VIXs) for equity markets in 14 developed and developing countries by using daily data between 17 March 2011 and 7 October 2016. These 14 countries include Brazil, Canada, China, France, Germany, India, Japan, Mexico, Russia, South Africa, Sweden, Switzerland, UK and US. Wavelet multiscale decomposition is used to obtain 6 different frequencies for Bitcoin and quantile regression is employed to examine whether Bitcoin hedge against global uncertainty. Results suggest for short-term frequencies; Bitcoin could be used to hedge against market risk for an upper quantile (bull regime) but not for lower quantile.

Bouri et al., (2016) employ dynamic conditional correlation model, GARCH(1,1)-DCC(1,1), to examine whether Bitcoin can be used to hedge against the stock, bonds, commodity, oil, gold and currency. Five stock indices represent stocks markets for US, UK, Germany, Japan and China. Both Morgan Stanley Capital International (MSCI) for Europe and Asia Pacific stocks are used to represent the world stocks. Standard &Poor's Goldman Sachs Commodity Index (S&P GSCI)and Pimco Investment Grade Corporate Bond Index Exchange-Traded Fund were used to representing commodity and bond market respectively. The exchange rate of US dollar against major foreign currencies is used to represent currency market. Both daily data and weekly data are used between the period of 18 July 2011 and 22 December 2015. Pairwise dynamic conditional correlations are examined between bitcoin and other assets. For daily data, bitcoin acts as a hedge against commodity index, Japanese stock and MSCI Pacific only. When weekly data was used, none of these has negative relationship with Bitcoin return. Bitcoin is found to be a hedge against Chinese stock when using weekly data. Therefore, hedging capability of Bitcoin changes if frequency changes. In this chapter, similar indices for the commodity, equity and currency markets will be used with GARCH-DCC model. But different frequency data will be used to examine whether the frequency of data matters.

Bouri et al., (2017b) examine whether Bitcoin can hedge against commodity index. As Bitcoin mining is related to energy consumption. The study focuses on investigating Bitcoin property against energy commodity. Asymmetric bivariate dynamic conditional correlation (ADCC) model is being used where bitcoin return is pairwised with each of the three commodity indices including commodity index in general, energy commodity index and non-energy commodity index. The conditional mean equation uses autoregressive moving average process. The asymmetric effect is included in variance equation. The following ADCC model is being employed:

$$r_t = \mu_t + wr_{t-1} + \varphi\varepsilon_{t-1} + \varepsilon_t \quad \textit{Equation 4.2.2.5}$$

$$h_t = c + a\varepsilon_{t-1}^2 + bh_{t-1} + \zeta\varepsilon_{t-1}^2 I_{t-1} \quad \textit{Equation 4.2.2.6}$$

where ζ measures the asymmetric effect h_t is the conditional variance, a and b parameters captures ARCH and GARCH effects. Daily data between 18/07/2010 and 28/12/2015 is used which includes the Bitcoin crash period at the end of 2013. Results suggest Bitcoin could hedge against commodity index and energy commodity index for the examined period and the period before Bitcoin crash. However, it does not exhibit hedge for the period after the crash.

4.2.3. Portfolio

Previous studies also investigate whether Bitcoin should be included in a portfolio for an investor who considers traditional assets (equity and bonds) and alternative investments such as commodity, currency, real estate and hedge fund in their portfolio. Their results are consistent and suggest Bitcoin should be added to a portfolio. Chowdhury (2014) examine whether Bitcoin should be included in a US investor's portfolio. Both traditional assets and alternative investments were considered with weekly closing prices for between 01/02/2010 and24/01/2014. These assets and investments include equities, bonds, fiat currencies and commodities which were represented by S&P 500 index, Barclays US Aggregate Bond index, Euro & Pound, crude oil (NYMEX) and gold price (COMEX) respectively. First, estimation was performed within an in-sample setting and out-of-sample setting. For the in-sample setting, the regression-based spanning technique was used to test for mean-variance spanning and non-mean-variance spanning in order to examine if the addition of Bitcoin to a traditional asset portfolio improves investment opportunity. The out-of-sample testing used Sharp ratios to test whether results are consistent with in-sample testing. The optimal portfolio was obtained by considering the higher order moments of returns distribution of the assets. Results suggest within the in-sample setting, Bitcoin offers diversification benefits to investors. But under the out-of-sample framework, a portfolio without Bitcoin has better performance. Briere et al., (2015) employed mean-variance spanning test to confirm Bitcoin offer diversification benefits to a portfolio for a US investor who considers both traditional assets and alternative investments in his portfolio, by using weekly data between 23/07/2010 and 27/12/2013.

Gangwal (2016) analyses the effect of including Bitcoin in a portfolio for the international investor. The investor is considered to hold both traditional assets and alternative investments which were represented by S&P500, Gold price, Oil index, MSCI world real estate index, Barclays Bond index, MSCI emerging world index and Baltic dry index. An optimal portfolio is constructed by using Sharpe ratio which used calculated the standard deviation and means of these daily data between 02/07/2010 and 02/08/2016. Results suggest high Bitcoin volatility is offset by high returns. Hence a portfolio with Bitcoin included gives higher risk-adjusted return.

Eisl et al., (2015) argue that Bitcoin return is not normally distributed. Hence conditional value-at-risk framework is adopted rather than mean-variance approach. Similar to other studies, both traditional assets and alternative investments such as currency, equity, bond, commodity and real estate are being considered with the same sample period as Bitcoin return which is between 18/07/2010 and 30/04/2015. Results show Bitcoin should be added to an optimal portfolio which gives a better risk-return ratios.

No study has considered a portfolio with only cryptocurrencies. This is the first study that considers two cryptocurrencies as a portfolio and examines their short and long-term relationship. It is important to include Bitcoin in the cryptocurrency portfolio because cryptocurrency market is still at its early stage and will be further developed in the future. Until then, it is important to treat Bitcoin as the bench market of the market because it is the first cryptocurrency that uses blockchain technology. Although some people do not believe in Bitcoin itself because it has old technology. However, no one denies the technology of blockchain which lead to creation of many other cryptocurrencies based on the blockchain technology. In addition, many cryptocurrencies could only be purchased with a few major cryptocurrencies where Bitcoin is one of them. Therefore it is important to include Bitcoin in a cryptocurrency portfolio. This method will be employed to more cryptocurrencies so that the dynamic relationship among different cryptocurrencies could be examined. For illustration purpose, only two of the cryptocurrencies, Bitcoin and Litecoin will be considered in the analysis.

4.3. Research Questions

In the last chapter, the dynamic relationship between Bitcoin and Litecoin returns are examined. Results suggest there exist significant volatility transmission for the conditional mean equation and significant spillover effect for conditional variance-covariance equation between two cryptocurrency markets. Although Bitcoin, as the first cryptocurrency has strengthened its market position since the invention of initial coin offering. In most of the initial coin offering, newly generated cryptocurrencies are sold to investors in exchange for other cryptocurrencies such as Bitcoin. Users who use cryptocurrencies as an alternative currency for many reasons including low transaction fee, quick payment speed, anonymous and irreversible payment (good for merchants). A cryptocurrency user who uses cryptocurrencies for daily transaction might wish to reduce the level of fluctuation to the minimum so that they could maintain the value of their cryptocurrency over a certain period of time. Meanwhile, they would like to continue using cryptocurrency as currency as it has some advantages over fiat currency. However, the fluctuation of cryptocurrencies is more volatile than fiat currency.

The main research question of this chapter is whether a cryptocurrency user can continue the benefit from using cryptocurrencies while avoiding the risk of fluctuation for holding them. A second research question is whether an investor could hold a portfolio of cryptocurrency that has same hedging capability against traditional assets. Based on the previous studies, Bitcoin acts as a diversifier in most of the time instead of a hedge against traditional assets. However, no study has examined the hedging capability of Litecoin. Therefore, the hedging capability of Litecoin will also be examined. If result suggests there exist hedging capability of the cryptocurrency portfolio, then the optimal weight for holding Bitcoin and Litecoin will be calculated in order to construct a portfolio. In the end, the hedging effectiveness of the cryptocurrency portfolio will be examined. By using the same methodology that is used in Bouri et al., (2016), this study will also examine whether the frequency of data matters in examining the hedging capability of cryptocurrencies by using daily without the weekend to compare with the results from Bouri et al., (2016). To the best of my knowledge, this is the first study uses bivariate GARCH-DCC model for constructing a cryptocurrency portfolio between Bitcoin and Litecoin and exploring its hedging capability, optimal weights and hedging effectiveness.

4.4. Methodology

4.4.1. Constant conditional correlation (CCC)

Bollerslev (1990) proposes the first conditional correlation model which focuses on the correlation of assets rather than covariance of assets. The conditional variance is estimated indirectly via conditional correlation. Assume $\sigma_{ij,t}$ is the covariance between asset i and j and $\sigma_{i,t}^2$ is the conditional variance from univariate GARCH. The constant correlation between two assets can be denoted as ρ_{ij} which has the following formula:

$$\rho_{ij} = \frac{\sigma_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$$

Equation 4.4.1.1

$$\sigma_{ij,t} = \rho_{ij}\sigma_{i,t}\sigma_{j,t}$$

A 2×2 correlation matrix could be expressed as follows:

$$P = \begin{pmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{pmatrix}$$

Equation 4.4.1.2

In terms of matrices, the temporal variation only depends on conditional variance as the

$$\mathcal{H}_t = D_t^{1/2} P D_t^{1/2}$$

Equation 4.4.1.3

where D_t represents the diagonal matrix of conditional variances and P represents the conditional correlation matrix of innovation terms from the univariate GARCH. They are both positive definite suggesting variance-covariance matrix is also positive definite. However, such model is too restricted and studies show it is not plausible to assume constant correlation for most of the financial data. Both Engle and Sheppard (2001) and Tse and Tsui (2002) developed time-varying conditional correlations which are called dynamic correlation model and time-varying correlation model respectively. They have different concept and will be introduced separately.

4.4.2. Dynamic conditional correlation (DCC)

Engle and Sheppard (2001) introduced the dynamic conditional correlation model where covariance matrix is decomposed into conditional standard deviations, D_t, and time-variant correlation matrix, P_t. As the conditional correlation becomes time-variant, the above expression changes to the following:

$$\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$$

Equation 4.4.2.1

which has the following matrix form:

$$P_t = Diag(Q_t)^{-1/2} \times Q_t \times Diag(Q_t)^{-1/2}$$

Equation 4.4.2.2

$$Q_t = (1 - \zeta_1 - \zeta_2)\bar{Q} + \zeta_1(u_{t-1}u_{t-1}^T) + \zeta_2 Q_{t-1} \quad \text{Equation 4.4.2.3}$$

where $\bar{Q}$ represents the unconditional covariance matrix of standardized residuals from univariate GARCH, $u_t = \{\varepsilon_{i,t}/\sigma_{i,t}\}_{i=1,\dots,n}$ and $Diag(Q_t)^{-1/2}$ represents the diagonal elements of diagonal matrix Q_t. Conditional correlation matrix P_t would be positive definite from estimation if $0 < \zeta_1, \zeta_2 < 1$ and $\zeta_1 + \zeta_2 < 1$.

4.4.3. Optimal portfolio weight

The conditional volatilities from DCC model would be used for constructing optimal portfolio weights (Kroner and Ng, 1998). The optimal weight would be estimated as the following:

$$w_t = \frac{h_t^b - h_t^{bl}}{h_t^l - 2h_t^{bl} + h_t^b} \quad \text{Equation 4.4.3.1}$$

Where

$$\begin{gathered} w_t = 0, if\ w_t < 0 \\ w_t = w_t, if\ 0 \le w_t \le 1 \\ w_t = 1, if\ w_t > 1 \end{gathered} \quad \text{Equation 4.4.3.2}$$

When constructing portfolio weights between Bitcoin and Litecoin. The letter w_t represents the weight of Litecoin in Bitcoin-Litecoin portfolio at time t. Both h_t^b and h_t^l represent conditional variance of Bitcoin and Litecoin returns while h_t^{bl} represents the conditional covariance between Bitcoin and Litecoin returns. Therefore, the weight of Bitcoin is equal to $1 - w_t$.

4.4.4. Hedging error

The effectiveness of hedging for the cryptocurrency portfolio could be examined via realized hedging errors:

HE= [VAR(Bitcoin asset)-VAR(hedged portfolio)]/VAR(hedged portfolio)

$$HE = \frac{VAR(b) - VAR(bl)}{VAR(bl)}$$ Equation 4.4.3.3

Where the VAR(bl) represents the variance of return on Bitcoin-Litecoin portfolio and VAR(b) represents the variance of Bitcoin return. A higher hedge error ratio suggests better hedging effectiveness in terms of portfolio's variance reduction. In another word, the Bitcoin-Litecoin portfolio could be constructed as a hedging strategy.

4.5. Data

4.5.1. Description of data

Daily closing prices have been collected for Bitcoin and Litecoin from BTC-e exchange market in terms of US dollar between the periods of 17/July/2013 and 25/July/2017. In addition, the price indices for commodity and equity have been collected via Datastream as well as 10 exchange rates in terms of US dollar and a trade-weighted US dollar index which is the value of US dollar relative to other world major currencies. All daily data collected from Datastream do not have weekend data. Therefore, this chapter will remove weekend data for both Bitcoin and Litecoin for analysis. The structure of the data will also allow us to examine the importance frequency of data when testing the hedging capability of cryptocurrency against traditional assets. In total, 28 time series data were collected from Datastream including 9 commodity price indices, 8 equity price indices and 10 exchange rates in terms of US dollar and one US dollar index.

All commodity series are collected from S&P GSCI (Goldman Sachs Commodity Index) from Datastream include S&P GSCI indices in general, gold, metal, agriculture, precious metal, energy, crude oil, biofuel and natural gas. All equity indices are collected from MSCI (Morgan Stanley Capital International) indices from Datastream include MSCI indices for the world, emerging countries, AC countries (23 major developed and 24 major emerging countries), the Europe, the Pacific region, the USA, Japan and China. All currency exchange rates time series are reuters benchmark rates collected from Thomson Reuters from Datastream include Japanese Yen/US dollar, Chinese Yuan/ US dollar, Australian dollar/ US dollar, Canadian Dollar/US dollar, UK sterling/US dollar, Euro/US dollar, Swiss Franc/US dollar, Indian Rupee/US dollar, South Africa Rand/US dollar, Brazilian Real/US dollar and US dollar index against a basket of major currencies. Note that, the positive correlation between cryptocurrencies and the above exchange rates could be reversed if the exchange rate is expressed the other way round. Cryptocurrency might be better than financial derivatives with standard currency for risk management because it is less correlated with traditional financial assets.

Diagram 1 shows the price movement for Bitcoin and Litecoin in the past four years. It is shown that Bitcoin price has increased exponentially since 2015 while Litecoin experienced a rapid and fairly steady increase of price in 2017. Diagram 2, 3 and 4 show the price indices for commodity, equity and currency assets. Most of the S&P GSCI decrease since 2013 until 2015 where majority of the commodity price indices started to raise again. Although MSCI differs a lots among themselves. But majority of them start low in 2013 and ended high in 2017. It is also clear that some of the MSCI experienced a rapid drop in 2016 around June. Notice that the last graph in diagram 4 shows the US dollar index based on the year of 1997. All exchange rates have similar trend in the sense that majority of them start with low value in 2013 and gradually increase to peak in around 2016.

Descriptive statistics for all series are shown in the appendix. Among all series, Bitcoin and Litecoin log price have the largest volatility in terms of standard deviation when comparing to their own price series. Some of the series have skewness and excess kurtosis values close to zero. In addition, the p-values for Jarque-Bera test results suggest the null hypothesis could not be rejected for three commodity return indices including MSCI world price index, MSCI Asia world price index and MSCI USA price index indicating such series are normally distributed. However, in order to have coherent data analysis, all time-series data will be transformed into logarithm form.

4.5.2. Unit root test

Before analyzing the research question, the Augmented Dickey Fuller (ADF) unit root test has been carried out for each of the time series data in order to check for stationarity of each time series. The following table shows the augmented dickey fuller unit root test results for each time series. The first column display the name of each time series. The second column of the table shows the unit root test results when only intercept term is considered in the testing equation at level. The third column shows both intercept and trend are being considered in the testing equation at level. The final column shows the unit root test results after first differencing.

Table 2: ADF unit root test for all variables in logarithm form. *,** and *** denotes 10%, 5% and 1% significant level respectively.

Notation	Name of variables	intercept	Intercept and trend	First differenced
Aa	S&P GSCI Commodity Spot	0.6206	0.9475	0.0000
Ab	S&P GSCI Gold Spot	0.1114	0.3214	0.0000
Ac	S&P GSCI Industrial Metals Spot	0.6666	0.9616	0.0000
Ad	S&P GSCI Agriculture Spot	0.3301	0.5153	0.0000
Ae	S&P GSCI Precious Metal Spot	0.1365	0.3555	0.0000
Af	S&P GSCI Energy Spot	0.6006	0.9100	0.0000
Ag	S&P GSCI Crude Oil Spot	0.5514	0.9073	0.0000
Ah	S&P GSCI Biofuel Spot	0.2310	0.5431	0.0000
Ai	S&P GSCI Natural Gas Spot	0.4175	0.6196	0.0000
Ba	MSCI WORLD	0.2771	0.2765	0.0000
Bb	MSCI EMERGING	0.5039	0.8734	0.0000
Bc	MSCI AC WORLD	0.2855	0.3869	0.0000
Bd	MSCI EUROPE	0.2763	0.3368	0.0000
Be	MSCI PACIFIC	0.1337	0.3484	0.0000
Bf	MSCI USA	0.6239	0.1664	0.0000
Bg	MSCI JAPAN	0.3320	0.4230	0.0000
Bh	MSCI CHINA	0.5243	0.8122	0.0000
Ca	JAPANESE YEN/US DOLLAR	0.4422	0.8313	0.0000
Cb	CHINESE YUAN/US DOLLAR	0.9089	0.4952	0.0000
Cc	AUSTRALIAN DOLLAR/US DOLLAR	0.5331	0.9501	0.0000
Cd	CANADIAN DOLLAR/US DOLLAR	0.4704	0.1122	0.0000
Ce	UK STERLING/US DOLLAR	0.8732	0.9606	0.0000
Cf	EURO/US DOLLAR	0.6651	0.9264	0.0000
Cg	SWISS FRANC/US DOLLAR	0.0521*	0.0016***	0.0000
Ch	INDIAN RUPEE/US DOLLAR	0.2342	0.3880	0.0000
Ci	SOUTH AFRICA RAND/US DOLLAR	0.4323	0.8001	0.0000
cj	BRAZILIAN REAL/US DOLLAR	0.5956	0.9490	0.0000
Dc	US DOLLAR INDEX	0.6766	0.9591	0.0000

4.5.3. Data transformation

Results suggest majority of the time series have unit roots. Therefore, the returns indices will be used for analysis from these log price indices. The below diagram shows the return indices for Bitcoin, Litecoin, commodity, equity and currency.

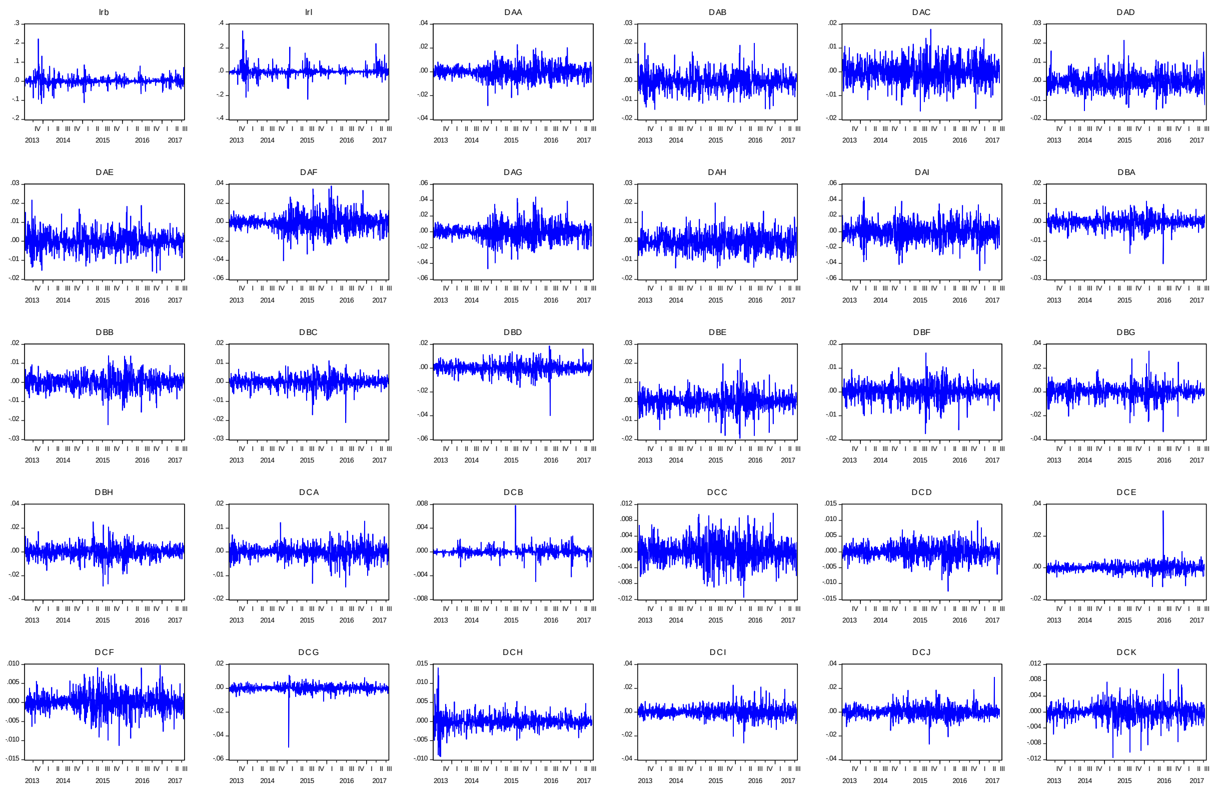


Table 3: Log of return for Bitcoin and Litecoin and price indices in logarithm form for commodity, equity and currency.

The above diagram shows many of the series have clustering effect which suggests volatility should be considered for data analysis. Descriptive statistics for these series are provided in the appendix. The standard deviation for both Bitcoin and Litecoin log returns suggest cryptocurrencies have higher volatility than traditional assets. Majority of commodity indices have positive skewness while the majority of equity indices have negative skewness. Although some of these skewness values are close to zero, the excess kurtosis is not close to zero. Therefore, none of the series rejects the null hypothesis of Jarque-Bera implies none of them is normally distributed.

4.5.4. Hypotheses

Hedging capability of Bitcoin against traditional assets has been discussed, but the economic theory behind it was not explained. This study mainly considers whether Bitcoin and Litecoin could hedge against traditional assets and will not try to explain the reason behind it either because there is no related theory is available for discussion. Therefore the main focus will be examining the correlation between cryptocurrency and traditional assets and see if this information will be useful for explaining the relationship of Bitcoin and Litecoin within the cryptocurrency portfolio.

In terms of commodity indices, Bitcoin and Litecoin prices are expected to be affected by energy, gas and oil prices because these are the raw material which could be used to generate electricity. In this study, these three types of commodity indices will be used to indicate the cost of generating electricity. If the commodity return goes down, then the commodity price goes down. The decrease in the cost of generating electricity will reduce the cost for miners for solving mathematical algorithm and forming a block into the blockchain. The increase in the number of miners will lead to more secured network and faster confirmation time which could attract more demand in Bitcoin or Litecoin. Therefore the prices for Bitcoin and Litecoin will go up followed by the increase in demand. Hence the return will also go up. Therefore, these returns are expected to be negatively correlated to Bitcoin, and Litecoin returns. Apart from the energy, gas and oil indices, the rest of the commodity indices are not expected to have a strong significant relationship with Bitcoin and Litecoin returns especially in the short run. If a significant relationship exists, then it is expected that the correlations are expected to be close to zero which could also be used for hedging. But these commodity indices will also be considered because one of the objectives of this chapter is to find the correlation between cryptocurrency and traditional assets. Therefore, the more series are considered, the more information will be provided for analysis.

Equity indices are expected to be more correlated with cryptocurrencies on average because over the past few years cryptocurrencies have been studied by more people and organization. The technology behind Bitcoin called blockchain has been explored more, and some companies even introduced the same kind of blockchain technology and building a cryptocurrency for different platforms which serve different purposes. Over the past few years, the information technology sector has grown rapidly where many companies and organization dedicate themselves to network security aspect. The blockchain technology provides a fast, convenient and secured network for all types of transactions and all types of platforms. Bitcoin is the first decentralized cryptocurrency introduced blockchain technology, and many newly released cryptocurrency could only exchange with Bitcoin and a few of other cryptocurrencies instead of fiat currency which further strength the position of Bitcoin in the cryptocurrency market. Therefore, cryptocurrency such as Bitcoin and Litecoin are not only digital currency or virtual assets anymore. Bitcoin presents a technology which is being used in many other aspects. Therefore, it is expected that there exist significant but weak correlations between cryptocurrency returns and equity return indices.

Given that majority of Bitcoin and Litecoin users obtain their cryptocurrencies via exchange markets using different fiat currency. Therefore, a change in exchange rate will lead slight adjustment of Bitcoin or Litecoin price within a very short period of time among exchange markets. Therefore, only a little or no correlation will be expected between fiat currency exchange rates and cryptocurrency prices. Although previous studies found a significant negative correlation between some exchange rates returns with Bitcoin return.

By forming a cryptocurrency portfolio and testing the correlation with traditional assets. It is possible to examine the relationship between Bitcoin and Litecoin in terms of market position. In terms of market capitalization, Bitcoin is the market leader. However, its market share is dropping since the features of newly generate cryptocurrencies attract more people. Therefore, in terms of features, Bitcoin does not have many advantages over many other cryptocurrencies. However, it is still reasonable to assume that if Bitcoin is the market leader and Litecoin is the follower when Bitcoin and Litecoin follow the leader-follower relationship. If a leader-follower relationship exists, then they will be positively correlated which could be examined via the coefficient of the lagged of another cryptocurrencies' returns just like the previous chapter. But in this chapter, another way to look at the correlation relationship is via the sign of coefficients of traditional assets. If Litecoin follows Bitcoin, then the correlation between Bitcoin and the traditional asset should be the same as the correlation between Litecoin and the traditional asset. Such results will only suggest both of them acts as diversifier within the cryptocurrency portfolio. However, if Bitcoin is positively correlated with a traditional asset but Litecoin is not correlated or negatively correlated with the traditional asset, then Bitcoin and Litecoin could also be a hedge against each other within the cryptocurrency portfolio.

4.6. Result analysis

As described in section 4.4, three types of traditional assets have been collected including commodity, equity and currency indices. In this chapter, three different cases will be considered in order to answer the research questions. Within each of these three cases, three types of traditional asset variables will be considered separately and form three sets of regressions for each case.

For the first two cases, the bivariate VARX-GARCH-DCC model will be employed, where the returns of Bitcoin and Litecoin are two endogenous variables and the traditional asset variables will be considered as exogenous variables. These two cases examine the hedging capability of cryptocurrencies against traditional assets by considering the correlation relationship between the traditional asset and the portfolio of Bitcoin and Litecoin.

In the first case (case 1), the whole list of each type of the traditional asset variables will be considered as exogenous variables in each regression. The first, second and third regressions use the list of commodity return indices, equity return indices and exchange rate return indices series and forming Model 1.1.1, Model 1.2.1 and Model 1.3.1 respectively.

In the second case (case 2), the first (set 2.1), second (set 2.2) and third (set 2.3) sets of the regressions also only consider commodity, equity and currency variables respectively. Within each of these sets, only one of the traditional assets will be considered as an exogenous variable in each estimated model. There exist 9 commodity variables, 8 equity variables and 11 currency variables. Therefore, the first, second and third sets consist 9 commodity-related models (called Model 2.1.i for i=1,..,9), 8 equity related models (Model 2.2.j for j=1,..,8) and 11 currency related models (Model 2.3.k for k=1,..,11) respectively.

The third case (case 3) employs both bivariate VAR-GARCH-BEKK and bivariate VAR-GARCH-DCC models in order to examine the correlation relationship between one of the cryptocurrency returns and one of the traditional assets returns. Unlike the first and second cases, the third case only considers the pairwise regressions that exclude any exogenous variables in the estimated models. Similar to the previous two cases, the third case considers six sets of models since there are three types of traditional assets and two kinds of methodology. For the bivariate VAR-GARCH-BEKK model estimation, the first, second and third sets of models include 9 commodity-related models (Model 3.1.i.B for i=1,..,9), 8 equity related models (Model 3.2.j.B for j=1,..,8) and 11 currency related models (Model 3.3.k.B for k=1,..,11) respectively. Notice that the capital letter "B" at the end of each model indicate BEKK methodology is being employed. For the VAR-GARCH-DCC model estimation, there exist another three sets of regressions which are 9 commodity-related models (Model 3.1.i.D for i=1,..,9), 8 equity related models (Model 3.2.j.D for j=1,..,8) and 11 currency related models (Model 3.3.k.D for k=1,..,11) respectively. Notice that the capital letter "D" at the end of each model indicate DCC methodology is being employed.

Before regressing the bivariate VARX-GARCH-DCC model for case 1 and case 2, the optimal lag length will be chosen for VAR model with Bitcoin and Litecoin returns being the endogenous variables. By choosing the maximum lag length to be 20, the Hannan-Quinn information criterion selects the optimal lag length to be 1. Although such information criteria is not efficient like AIC, it is more consistent than AIC. The Hannan-Quinn information criterion is suitable for this these two cases because many time series data will be examined separately. For all the estimated model, the quasi-maximum likelihood method is employed so that robust errors would be used and these consistent standard errors would be robust to non-normality. Therefore, only two diagnostic tests will be employed including the multivariate Q-statistics which is equivalent to the multivariate Portmanteau statistics and the multivariate ARCH-LM test will be used for the diagnostic test in order to examine whether there exist autocorrelation and ARCH effect in the estimated model. The main focus of this chapter is to examine the hedging capability of cryptocurrencies through conditional mean models. Therefore, the conditional variance models in either BEKK or DCC models will not be the main concern here as long as they are stable.

4.6.1. Case 1

Model 1.1.1, Model 1.2.1 and Model 1.3.1 are estimated using bivariate VARX(1,1)-DCC(1,1) model. Both Model 1.1.1 and Model 1.3.1 have convergence results while Model 1.2.1 does not have convergence results. Therefore, the correlation relationship between cryptocurrency and equity indices will be discussed in case 2 and case 3.

4.6.1.1. Model 1.1.1

Model 1.1.1 involves 9 commodity return indices series and the lags of both Bitcoin and Litecoin returns as explanatory variables. Results suggest each of the explanatory variables is significant in predicting the current returns for either Bitcoin or Litecoin. However, the sum of the coefficients of squared errors and lag of variance is not less than one in the conditional variance model. Therefore, integrated GARCH (IGARCH) with drift is employed. Notice that, for the IGARCH model, the mean reversion is not a property of the conditional variance anymore. The forecast of conditional variance tends to reflect more on the recent changes rather than the average changes over the sample period. As mentioned above, the main focus in this chapter is investigating the sign of coefficients in each explanatory variables and examine the correlation relationship between the explanatory variable with endogenous variable. Therefore, after applying IGARCH model for the conditional variance models, we investigate the coefficients of the explanatory variables in the conditional mean models.

The Q-statistics with the randomly selected lag length of 8 has a value of 46.672 which has a p-value of 0.045 which is less than the conventional significant level of 0.05. Therefore, the null hypothesis of no autocorrelation will be rejected at 5% level. The multivariate ARCH statistics has a value of 39.31 which has a p-value of 0.9994 which indicates lack of evidence to reject the null hypothesis.

As Table 1 shows, all the lags of Bitcoin and Litecoin returns are significant at 1% level in predicting current returns of Bitcoin and Litecoin. As shown in the previous chapter, the lags of Bitcoin have positive impacts on the current returns for both Bitcoin and Litecoin. While the lags of Litecoin have negative impacts on both Bitcoin and Litecoin current returns. In the first conditional mean equation, Bitcoin and Litecoin returns are negatively correlated while the second conditional mean equation suggests they are positively correlated. Since the evidence on the sign of the correlation between Bitcoin and Litecoin returns are mixed in this model, the correlation between Bitcoin and Litecoin will be further examined based on other regressions in case 2 and case 3. As described in the previous chapter, the lag of Litecoin return tends to have a smaller impact on Bitcoin current return when compared to the impact of the lag of Bitcoin return on Litecoin current return which has nearly 10 times greater impact. After employing IGARCH model for the conditional variance models, the exogenous variables from the commodity return indices remain significant in predicting current returns of Bitcoin and Litecoin.

Majority of the commodity return indices are significant in explaining the Bitcoin return at 1%, except for two variables including the comoil variable which is not significant in predicting Bitcoin return and the comgas variable which has p-value of 0.0569 suggesting the impact is significant only at 10% level. In comparison, there exist two variables that do not affect current return of Litecoin including the comgeneral and comgas variables. The comimetal variable is significant in explaining the current Litecoin return at 10% level, where the p-value is close to 0.05.

The coefficients on the rest of the exogenous variables suggest the comgold, comagric, compmetal, comenergy and combio are significant in explaining both Bitcoin and Litecoin returns at 1% level. Within these 6 variables, both comgold and combio variables are negative correlated with both Bitcoin and Litecoin current returns. The negative correlation relationship is stronger between these two commodities and Litecoin. Results suggest an increase of 1% in gold and biofuel returns in the previous period will lead to decrease of Litecoin current return by 1.48% and 0.64% respectively. Whereas the current returns of Bitcoin will only be reduced by 0.9% and 0.46%.

In addition, the Bitcoin return is negative correlated with both comgeneral and comgas variables. It was found that Bitcoin return has the strongest negative correlation with the comgeneral variable. Result suggests if the comgeneral is increased by 1%, then the Bitcoin return will be reduced by 1.44% on average. The negative correlation between Bitcoin return and the comgas is the weakest indicating an increase of 1% in natural gas return will lead to decrease of 0.06% in Bitcoin return. In contrast, the Litecoin return is negative correlated with the comoil variable which has coefficient of -0.329 suggesting a weak negative correlation as well. Based on the hedging definition provided in the introduction section, gold, biofuel, industrial metals, crude oil, natural gas assets are useful in hedging against the portfolio of Bitcoin and Litecoin.

Moreover, the comagric, compmetal and comenergy have a strong positive correlation with both Bitcoin, and Litecoin returns. The correlations between these 3 assets and Bitcoin return are consistent in the way that an increase in 1% of returns on each of these assets will lead to roughly 0.9% of the increase in Bitcoin returns. It is interesting that Bitcoin moves in the same direction as the precious metals on average because it might be a sign that Bitcoin is being treated as a substitute of gold just like other precious metals. Different precious metals have their own industrial purposes while Bitcoin also has its value in the payment system. Litecoin return also has a positive correlation with these 3 types of commodity assets but with a large range of the values of coefficients. Litecoin return has the weakest and strongest positive correlation with comenergy and compmetal variables respectively. Based on the definition of diversifier, these 3 types of commodity assets act as diversifiers instead of hedges against Bitcoin and Litecoin. Overall, the portfolio of all commodity assets is helpful in explaining the returns of Bitcoin and Litecoin. Each one of them has either diversifying or hedging capability against Bitcoin or Litecoin. However, by regressing all of these commodity assets simultaneously might lead to a biased result in deciding the pairwise correlation relationship between the cryptocurrency and the traditional asset. Therefore, more investigation will be carried out in both case 2 and case 3.

4.6.1.2. Model 1.2.1 and Model 1.3.1

Model 1.2.1 does not lead to convergence results if all of the equity indices are being regressed simultaneously. Therefore, the correlation between these equity return indices and cryptocurrency returns will be discussed in case 2 and case 3. For Model 1.3.1, both Bitcoin and Litecoin returns are being regressed on their own lags as well as the list of exchange rate return indices. However, the sum of coefficients on previous squared errors and variance is not less than 1. Therefore, IGARCH is employed in order to have a stationary GARCH process. The estimated model has three variables that are insignificant in explaining Bitcoin and Litecoin current returns. These three variables are exuk, exind and exafr which are the exchange rate of UK sterling, Indian Rupee and South Africa Rand against the US respectively.

Therefore, a restricted model has been compared with this unrestricted model by employing Wald test which has the null hypothesis of exuk=exind=exafr=0. The Chi-squared of 4.11 with three degrees of freedom has a p-value of 0.25 which is greater than 0.05 suggesting lack of evidence to reject the null hypothesis. F-statistics of 1.37 also suggests the same conclusion. Therefore, the restricted model is preferable. The exjap variable becomes insignificant in both conditional mean equations in the restricted model. Therefore, another Wald test is carried out, the Chi-squared of 1.39 with one degree of freedom has p-value of 0.238 which is greater than 0.05. Therefore, the results suggest removing the exjap variable from the restricted model. Finally, the restricted model with exjap=exuk=exind=exafr=0 is being examined. The multivariate Q-statistics with lag length chosen to be 8 has a value of 45.33 has associated p-value of 0.06 which is greater than 0.05. Therefore, the null hypothesis of no autocorrelation could not be rejected at 5% level. Moreover, the multivariate ARCH statistic has a value of 0.99 which indicate ARCH effect does not exist anymore. The coefficients on the past squared error and past variance are highly significant, and their sum is less than 1 which indicates a good persistence in the conditional correlation process. The results from the conditional mean model indicate the lags of Bitcoin and Litecoin return have positive and negative impacts on both Bitcoin and Litecoin current returns, which provide the same conclusion as in Model 1.1.1. For conditional variance equations, out of 7 exchange rate return indices, three of them have a significant relationship with Bitcoin return while 6 of them have a significant relationship with Litecoin return.

Three of the exchange rate return indices including exaus, excan and exeur have a significant impact on both Bitcoin and Litecoin current returns, which are Australian Dollar/US dollar, Canadian Dollar/US dollar and Euro/US dollar respectively. Among these three variables, only the excan and exeur variables have a negative correlation with both Bitcoin and Litecoin current returns. Results indicate an increase in 1% of excan variable will lead to a decrease of 0.26% and 0.36% decrease in Bitcoin and Litecoin returns respectively. A 1% increase in exeur variable will lead to 0.36%, and 2.66% decrease in Bitcoin and Litecoin returns respectively. These are the only two variables that are negatively correlated with Bitcoin return. In comparison, there exist another one variable, exbra, which is negatively correlated with Litecoin return. Among all the correlation relationships, the correlation between excan and

Litecoin return is the strongest. The Real/Dollar exchange rate return indice denoted by exbra, tends to have a smaller negative correlation with Litecoin return on average, where an increase of 1% in exbra with lead to reduce in Litecoin return by 0.26%.

4.6.2. Case 2

Although some of the variables of the exchange rate are removed from the regression in case 1 based on Wald test, all the exchange rate variables will still be examined again for robustness check in case 2. Moreover, the estimated results in case 2 can help to identify the comovement between Bitcoin and Litecoin via a triangular relationship with another traditional asset. Details will be given at the end of the discussion section.

In total, there are 28 estimated bivariate models for case 2. Each of these models employs VARX-DCC model and regress both Bitcoin and Litecoin returns on their own lags and one additional exogenous variable that is selected from the lists of the commodity, equity or exchange rate time series. All models will use IGARCH to ensure stable GARCH process. Since every estimated model uses quasi likelihood estimation, therefore normality diagnostic test is not needed. Only multivariate Portmanteau test and the multivariate ARCH test will be used to examine the property of standardized errors in each estimated model.

4.6.2.1. Set 2.1

As shown in Table 4, the Model 2.1.i involves 9 different VARX(1,1)-DCC(1,1) models where i=1,2,3…,9 indicate the estimated models with exogenous variables comgeneral, comgold, comimetal, comagric, compmetal, comenergy, comoil, combio and comgas respectively. An arbitrage lag length of 8 has been chosen when running the diagnostic tests. The Model 2.1.9 has a multivariate Q-statistic value of 47.09 with a p-value less than 0.05, which indicates there still exist autocorrelation. Results suggest the rests of the 8 estimated models for Model 2.1.i have smaller Q-statistics values and the corresponding p-values are greater than 0.05. Therefore the null hypothesis of no autocorrelation cannot be rejected at 5% level. Moreover, results suggest ARCH effect no longer appears in all of these 9 models. Similar to the findings from case 1, the lags of Bitcoin and Litecoin returns have the same effect on their current returns. Out of 9 commodity assets, only 6 of them are correlated with either Bitcoin, or

Litecoin returns. Most of them are correlated with Bitcoin return rather than Litecoin return. Except for the comagric variable which is positively correlated with both Bitcoin and Litecoin returns indicate an increase of agriculture return by 1% will lead to an increase of 0.22% and 0.30% increase in Bitcoin and Litecoin returns respectively. The coefficients on the other exogenous variables suggest general commodity return index, industrial metals, energy and crude oil return indices are positively correlated with Bitcoin returns. The only negative correlated commodity asset with Bitcoin is the natural gas where the result suggests an increase of 1% in natural gas return will lead to 0.07% decrease in Bitcoin return.

4.6.2.2. Set 2.2

As shown in Table 5, this set involves 8 different VARX(1,1)-DCC(1,1) models called Model 2.2.j where j=1,2,3…,8 indicates the estimated models with exogenous variables eqwor, eqeme, eqacw, eqeur, eqpac, equsa, eqjap and eqchi respectively. The models 2.2.2, 2.2.5 and 2.2.7 have Q-statistics of values 46.92, 46.85 and 47.12 respectively and the corresponding p-values are less than 0.05. Therefore, there exist autocorrelation in these models at 5% significant level. Except for these three estimated models, the diagnostic results for the other five estimated models in this set suggest no autocorrelation exist at 5% significant level. In addition, none of the estimated models has ARCH effect since the corresponding p-values are close to 0.99. Litecoin tends to have a more significant correlation with equity assets when compare to commodity assets.

However, there is only one negative correlation between Litecoin and equity asset which is the eqchi. Moreover, there are two positive correlation relationships with equity assets including eqwor and equsa. The equsa is also positive correlated with Bitcoin on average. Furthermore, results also suggest Bitcoin could hedge against eqeme, eqpac and eqchi since the coefficients are negative significant. Although there exist negative correlation, but the hedging effect is weak because the magnitude of these coefficients is relatively small. In order to examine the hedging effectiveness of cryptocurrencies on these equity assets, pairwise regressions between cryptocurrency and these equity assets will be estimated before calculating the realized hedging errors which represent the hedging effectiveness of a particular portfolio. If no negative correlation could be found between cryptocurrency and equity assets based on the pairwise regression, then there is no need to calculate the hedging effectiveness of a portfolio.

4.6.2.3. Set 2.3

As shown in Table 6, this set involves 11 different VARX(1,1)-DCC(1,1) models called Model 2.3.k where k=1,2,3…,11 indicate the estimated models with exogenous variables exjap, exchi, exaus, excan, exuk, exeur, exswi, exind, exafr, exbra and exusa respectively. The models 2.3.3, 2.3.4 and 2.3.8 have Q-statistics values of 46.55, 46.36 and 46.35 respectively with corresponding p-values less than 0.05, which suggest rejecting the null hypothesis of no autocorrelation. The ARCH test statistics results suggest no ARCH effects in these models. The diagnostic results for the rest of the estimated models reject the null hypothesis of no autocorrelation. The corresponding ARCH test statistics results suggest no ARCH effect is present in any of the rest of the estimated models.

Comparing currency assets to commodity and equity assets, more of the exchange rate time series have correlation relationships with both Bitcoin and Litecoin such as exjap, exchi, exswi and exusa which represent the Japanese Yen/US Dollar, Chinese Yuan/US Dollar, Swiss Franc/US Dollar and the US dollar index respectively. All of these four exchange rates variables are positive correlated with both Bitcoin and Litecoin returns which could imply both Bitcoin and Litecoin are moving in the same direction on if the magnitude of the coefficients are not large. Detail explanation will be given in the HYPOTHESIS SECTION.

Chinese Yuan/US Dollar, exchi, has the strongest positive relationship among all traditional assets and suggest a slight movement in the return of Yuan/Dollar such as 1% increase will lead to 1.80% and 1.88% increase in Bitcoin and Litecoin returns. This is interesting because China has one of the biggest cryptocurrency exchange platforms in the world and the correlation might have some implications. Unlike free-floating US Dollar, Chinese Yuan tends to have smaller variation. An increase in the Yuan/Dollar could suggest either a depreciation in Yuan or appreciation in Dollar. If Yuan depreciates, Chinese investors will tend to exchange their home currency for other currency to avoid lost in currency value. If Dollar appreciates, then investors might be attracted to Dollar and even invest in other US traditional assets such as US stock. Over the examined sample period, China’s stock market has experienced a burst of the stock bubble at the end of 2015 and the stock market index has been remained low compare to stock index in 2015. The US dollar started to appreciate against Chinese Yuan in 2016. However, the Chinese government started to restrict Chinese investors to purchase foreign currencies such as US dollar in 2016. Each of the individual investors has only $50,000 worth of value of quota for purchasing foreign currencies each year. Therefore, such policy limits many investors to sell their Chinese Yuan for foreign currency. However, there was no limitation on exchanging for cryptocurrency in the exchange markets. In addition, the cost of purchasing and trading cryptocurrency is relatively low which could attract many investors from purchasing cryptocurrency such as Bitcoin. Therefore, an increase in exchi will lead to increase in Bitcoin return could be seen as the purchasing power from the Chinese investors.

Exchange rate return indices tend to have a larger impact on Litecoin than Bitcoin returns since the correlation between returns of Litecoin and exchange rate are stronger. Especially for the relationship with the US dollar could be examined directly via the US dollar index. Results suggest an increase of US dollar index return by 1% will lead to increase in both Bitcoin and Litecoin returns by 0.45% and 0.71% respectively. This might due to the appreciation of the US dollar and attracts many Chinese investors to exchange their home currency for either US dollar or other assets such as cryptocurrency. Moreover, there exist one negative correlation between the exchange rate return indices, which is the correlation between Brazilian Real/US Dollar and Litecoin which suggests Litecoin could be hedged against Real/Dollar.

Instead of moving in the opposite direction with exchange rates of fiat currencies, both Bitcoin and Litecoin have a relatively strong positive correlation with these exchange rates when compare to commodity and equity assets. This is not surprised because most of the cryptocurrency investors tend to purchase cryptocurrencies rather than mining them whereas the latter method would take a longer period of time to make a large profit. Or the cost of mining would be too high if investors only want to hold them for a short period of time. If the spot rate between home currency and US dollar increases, then a value of home currency depreciates when compared to US dollar. This could be due to real depreciation in home currency or appreciation in US dollar. Either way, investors might consider of selling their home currency for other investment instruments in order to avoid losing in the values of currencies. Some investors might choose cryptocurrencies such as Bitcoin and Litecoin as alternative investments. The effect is stronger for the currencies of the developing countries including China and Brazil.

4.6.3. Case 3

The estimated models in case 3 could be classified into two groups. The first group uses VAR-GARCH-BEKK model while the second group uses VAR-GARCH-DCC model. The letters B and D in the estimated models in case 3 represents the corresponding models are estimated using VAR-GARCH-BEKK and VAR-GARCH-DCC models respectively. Both groups examine the pairwise relationship between traditional assets and cryptocurrency assets. However, results suggest only the significant variables from the estimated models in case 2 remain significant in case 3. Most of the insignificant variables from the estimated models in case 2 does not lead to convergence results in the estimation in case 3. Therefore, only 24 pairwise relationships will be examined. Out of 24 estimated models, 7 of them are pairwise regressions between commodity and cryptocurrency assets including 6 regressions between Bitcoin and the commodity assets, 7 of them are related to equity assets including 4 regressions between Bitcoin and the equity assets and 10 of them are related to currency assets where half of the pairwise regressions are between Bitcoin and the currency assets.

In this section, BEKK model could be used to examine whether there exists spillover effect in the variance from the traditional assets on cryptocurrencies. In addition, the correlation relationship will be examined via conditional mean models. Since BEKK assumes constant correlation on average, therefore it is important to have a stable long-run relationship between returns of traditional assets and cryptocurrencies. However, the main focus in this section is still the results from the conditional mean equations where we examine the correlation relationship between traditional and cryptocurrency assets via the coefficients values of the parameters in the conditional mean equations. Furthermore, the DCC model will be employed for robustness check. Given that the cryptocurrency market has much smaller market capitalization than traditional assets such as commodity, equity and fiat currency. This section mainly observes the correlation between cryptocurrency and traditional assets and the Granger causality and spillover effect from the traditional assets on either Bitcoin or Litecoin in terms of returns.

Before estimating VAR-GARCH-BEKK(1,1) or VAR-GARCH-DCC(1,1) models, the optimal lag length will be chosen for each model. With maximum lag length chosen to be 12, the optimal lag length will be chosen according to AIC. For the commodity assets, six variables including comgeneral, comimetal, comagric, comenergy, comoil and comgas will pairwise with lrb, and only the comagric variable will pairwise with lrl. For the equity assets, five variables including eqeme, eqpac, equsa and eqchi will pairwise with lrb and three variables including eqwor, equsa and eqchi will pairwise with lrl. For the currency assets, four variables including exjap, exchi, exswi and exusa will pairwise with both lrb and lrl separately to form 8 pairwise regressions. In addition, the exaus and exbra variables will pairwise with lrb and lrl respectively to form another two regressions. Models with no convergence estimation will not be interpreted here. The quasi-maximum likelihood estimation will be employed in both types of models.

4.6.3.1. VAR-BEKK

This section illustrates the results from VAR-BEKK(1,1) models. For the commodity assets, significant correlation relationships could be found between lrb and two variables including comimetal amd comagric. The optimal lag lengths were chosen to be 1 for these models according to AIC. All these three estimated models are stable in the long run, and significant spillover effect could be found among these three models. The dominant root for these three models is 0.998 and 0.975 respectively, which are all less than unit root. Moreover, the Q-statistics for these three models give values of 28.45 and 25.89 with corresponding p-values of 0.64 and 0.17 respectively. The ARCH test statistics give values of 41.96 and 62.41 with corresponding p-values of 0.60 and 0.78 respectively. Results suggest none of these models exists autocorrelation and ARCH effect. For pairwise regression between lrb and comimetal, the lag of comimetal is positively correlated with lrb in the way that an increase of 1% in comimetal will lead to 0.19% increase in lrb. The pairwise regression between lrb and comagric has a slightly greater correlation, an increase of comagric by 1% will lead to increase of lrb by 0.31%. No negative correlation could be found between commodity assets and Bitcoin. Moreover, it is expected that the lag of Bitcoin return does not have any impact on current returns of these three commodities. The rest of the commodities do not have significant correlation relationship with Bitcoin in terms of returns. Also, results indicate no convergence results could be estimated using VAR-GARCH-BEKK for the pairwise regression between comagri and lrl.

For equity assets, only two pairwise regressions indicate significant correlation relationship. These two pairwise regressions are between Bitcoin and MSCI pacific as well as the Litecoin and MSCI China in terms of returns. The Q-statistics values for these two models are 38.89 and 22.62 with associated p-values of 0.19 and 0.89 which indicate there is no autocorrelation in these estimations. In addition, the ARCH test statistics give values of 76.96 and 51.30 with corresponding p-values of 0.32 and 0.97 which indicate no ARCH effect exist in these two estimations. The optimal lag length for lrb and eqpac pairwise regression is chosen to be four. Only the first lag of eqpac has significant relationship with lrb. The negative correlation suggest an increase of eqpac by 1% will lead to Bitcoin return decrease by 0.19%. The dominants root for stability test is 0.985 which is less than 1 indicating the relationship is stable even in the long run. However, the spillover effect is not found to be significant. Based on the definition of hedge asset, Bitcoin could be used to hedge against MSCI pacific index in terms of returns. Results from the second regression indicate the first and second lags of MSCI China return indices have a negative and positive impact on Litecoin current return. Therefore, the evidence is mixed so that it is difficult to judge whether Litecoin could be hedged against MSCI China index. Moreover, the spillover effect are not significant in this regression either.

For currency assets, out of five pairwise regressions associated with Bitcoin, only two regressions indicate significant relationship which is between lrb and currency assets including exjap and exchi. An increase of 1% in exjap will lead to 0.31% increase in lrb in the next period. A stronger correlation could be found between lrb and exchi, where 1% increase in exchi will lead to 1.1% increase in lrb in the next period. In contrast, similar effects could be observed between the Litecoin and currency assets. An increase in exjap or exchi by 1% will lead to increase of lrl by 0.33% and 1.0% respectively. In addition, the third and sixth lags of exswi have negative impact on lrl where 1% increase in the third and sixth lags of exswi will lead to decrease of 0.33% and 0.27% in lrl.

4.6.3.2. VAR-DCC

For robustness check, the VAR-DCC models are employed for the same pairing assets. Majority of the estimated models do not lead to convergence results. For pairwise regressions between commodities and cryptocurrencies. Results indicate lrb is positive correlated with both comimetal and comagric where 1% increase comimetal and comagric will lead to 0.17% and 0.24% increase in lrb. Therefore, DCC results are in line with the BEKK results for these two variables. No significant relationship could be found between Litecoin and commodity assets. For pairwise regressions between equity and cryptocurrency assets, the only significant correlation relationship could be found between lrl and eqchi where 1% increase in the first and second lags of eqchi will lead to decrease of 0.33% and increase on 0.25% in lrl in the next period respectively. Therefore, these results based on DCC method are consistent with the results using VAR-GARCH-BEKK. For currency assets, exjap remains to have a positive impact on lrb while exchi remains to have a positive impact on lrl with greater magnitude. An increase in exchi by 1% will lead to increase of lrl by 2.0%. This result is in line with the results in case 2, where changes of value in Chinese Yuan/US Dollar will have a significant positive impact on returns of cryptocurrencies. Results from this group of estimation, none of the commodity, equity and currency assets could be a hedge against Bitcoin nor Litecoin in terms of returns.

4.6.4. Hedging portfolio

A portfolio of one cryptocurrency and one traditional asset could not be constructed based on the results given in the last section above. Since one of the contributions of this study is to examine whether Bitcoin and Litecoin could be hedged against each other. In the following, a portfolio of Bitcoin and Litecoin will be constructed.

Although conditional covariance could not be obtained directly from the estimation like BEKK model. But it could be model via the following formula:

$$h_t^{bl} = \rho * \sqrt{h_t^b} * \sqrt{h_t^l}$$

Equation 4.6.4.1

By constructing a portfolio of Bitcoin and Litecoin. We first examined their correlation relationship which is not always negative correlated. However, in some cases, their correlation is negative. As one of the research question is to examine the hedging capability of a cryptocurrency portfolio. In the following, the optimal weights for both Bitcoin and Litecoin will be calculated for each period. According to Kroner and Ng (1998), if an investor wants to minimize the risk of the cryptocurrency portfolio without reducing its expected returns. Then the below optimal portfolio weight could be obtained for Litecoin, whereas the optimal portfolio weight for Bitcoin is equal to $1 - w_t$.

$$w_t = \frac{h_t^b - h_t^{bl}}{h_t^l - 2h_t^{bl} + h_t^b}$$

Equation 4.6.4.2

Based on the optimal weight series calculated for both Bitcoin and Litecoin. The effectiveness of hedging for the portfolio could be examined via the realized hedging errors which have the following formula:

$$HE = \frac{VAR(b) - VAR(bl)}{VAR(bl)}$$

Equation 4.6.4.3

The results for the hedging error is equal to 0.00085 which implies a very low level of hedging effectiveness. This result is consistent to the estimated results among Model 1, Model 2 and Model 3, where the correlation relationships between Bitcoin and Litecoin is not clear. This method suggests the volatility of including Litecoin in the portfolio creates higher risk.

4.6.5. Hypotheses discussion

1. Can cryptocurrency hedge against traditional assets?

Throughout the three cases, both Bitcoin and Litecoin have been used to examine the relationship between commodity, equity and currency assets. Only one traditional asset is found to have a negative correlation with Bitcoin return across three cases, which is the natural gas return index. Although this result is consistent with three different sets of modelling. It is not consistent when DCC model is employed rather than BEKK in the third case. The rest of the negative correlation relationship between cryptocurrencies and traditional assets are not consistent across different sets of modelling. However, the results for the first set of modelling suggest commodity in general, gold, industrial metal, biofuel and natural gas could be hedged against cryptocurrency if 9 commodity assets are being considered as a portfolio. Results from the third set of estimation in case 1 suggest Canadian dollar, euro could be hedged against both Bitcoin and Litecoin if the 11 currency assets are being as a portfolio. Therefore, if Bitcoin and Litecoin are being treated as a portfolio while the commodity and currency assets are being treated as another two portfolios, then hedging capability could be found in cryptocurrencies. The cryptocurrency portfolio of Bitcoin and Litecoin has strong hedging capability against gold and biofuel commodities.

In case 2, both Bitcoin and Litecoin are still be treated as a portfolio, but instead of examining the portfolios that contain commodity, equity and currency assets, an individual one of the traditional assets will be used to examine the hedging capability of cryptocurrencies. Results indicate within the cryptocurrency portfolio, Bitcoin could hedge against comgas, eqeme, eqpac and eqchi while Litecoin could hedge with eqchi and exbra. Therefore, the cryptocurrency portfolio could be useful in hedging against eqchi because both Bitcoin and Litecoin are negative correlated with eqchi in this case.

In case 3, pairwise regressions are estimated so that individual asset is considered instead of a portfolio when examining the hedging capability of cryptocurrencies. Results indicate Bitcoin could only hedge against eqpac while Litecoin could hedge against both eqchi and exswi when VAR-GARCH-BEKK is employed. No negative correlation could be found if VAR-GARCH-DCC is employed. The results between lrb and eqpac is reliable because it has been tested that the correlation relationship remains stable even in the long run and the diagnostic test results suggest the corresponding standardized errors are white noise and are robust to non-normality.

2. Can Bitcoin and Litecoin be hedged against each other?

Both case 1 and case 2 results are useful in answering this hypothesis. Based on the definition of hedge asset. Bitcoin and Litecoin has to be negatively correlated on average. One way of examining such a relationship is to look at the coefficients of the lags of Bitcoin or Litecoin. If these are negative, then they are said to be negative correlated. However, such results might not be consistent because some of the lags of cryptocurrency returns might have opposite impacts on the current returns of another cryptocurrency. Another way of observing the correlation relationship is to include a third asset and form a triangular relationship. However, if a traditional asset has a significant relationship with the cryptocurrency, and the impact from the traditional asset is large in contrast to the relationship between Bitcoin and Litecoin which dominates the triangular relationship. Then this method will not give an accurate conclusion. In another word, if the magnitudes of the coefficients on the lags of traditional assets are large, then it is not reliable to examine the relationship in this way. However, if the correlation is small but significant, then the sign of coefficients of the lags of traditional assets on current returns of cryptocurrencies could be useful to decide the relationship between Bitcoin and Litecoin. The results from case 1 and case 2 suggest only Gold, Biofuel, Austrailian dollar/US dollar, Euro/US dollar and MSCI China have a significant relationship with both Bitcoin and Litecoin. However, the magnitudes of the coefficients are greater than 0.5 in most of them, which suggest an increase in 1% of these traditional assets could lead to more than 0.5% changes in both Bitcoin and Litecoin. This impact is fairly strong which might imply the traditional asset is dominating in the triangular relationships. When excan is included in this triangular relationship, the coefficients suggest an increase in excan by 1% will lead to decrease of Bitcoin and Litecoin returns by 0.258% and 0.364%. For MSCI USA, the impacts on both Bitcoin and Litecoin returns are smaller, an increase in 1% of equsa will lead to increase of lrb and lrl by 0.288% and 0.335% respectively. Finally, the Model 2.2.8 suggests if eqchi increases by 1%, then lrb and lrl will be reduced by 0.144% and 0.280%. All these results suggest Bitcoin and Litecoin move in the same direction on average. By looking at these coefficients, it seems that Litecoin is easier to be affected by traditional assets than Bitcoin. This makes sense because the Bitcoin market capitalization is much larger than Litecoin and if they are moving in the same direction on average, it is likely that Litecoin is a follower of Bitcoin since Bitcoin is the first decentralized cryptocurrency.

3. How effective is the hedging between Bitcoin and Litecoin?

Before calculating the realized hedging errors in order to present the hedging effectiveness of a portfolio. It is important to find some evidence which suggests there is negative correlation between these assets. However, based on the DCC estimated results, no negative correlation relationship could be found. Given that, this is one of the research questions in this chapter. Therefore, the hedging effectiveness of Bitcoin and Litecoin portfolio has been examined. The results from the hedging effectiveness section suggest Bitcoin and Litecoin do not form a good hedging portfolio. This finding is consistent with the findings found in the second hypothesis. Although Litecoin is more efficient is mining and making transactions than Bitcoin. It does not seem to be able to compete with Bitcoin. This is because Bitcoin being the first cryptocurrency has its own special meaning. For example, many initial coin offering requires investors or cryptocurrency users to purchasing well-known cryptocurrency in exchange for those new cryptocurrency. Bitcoin has been used in many initial coin offering which strengthens its market position. As technology and knowledge in cryptocurrency develop, cryptocurrencies with better feature will be generated. Therefore, Litecoin could be replaced easily. However, Bitcoin could not be replaced because it was the first decentralized cryptocurrency. Although it's not as efficient as some of the other cryptocurrencies, its market capitalization provide a strong and secured network for Bitcoin because more miners are maintaining the network.

4.7. Conclusion

This chapter examines the hedging capability of Bitcoin against another cryptocurrency, Litecoin. In addition, the hedging capability of Litecoin against traditional assets is being examined for the first time. Results suggest both Bitcoin and Litecoin could hedge against traditional assets. In line with previous study from Bouri et al., (2016), Bitcoin is negatively correlated with Chinese stock where Bouri uses weekly data. Bitcoin does not correlate with Japanes stock and MSCI pacific where Bouri uses daily data. This evidence suggest the same findings even different frequency of data is used. Moreover, in line with Bouri et al., (2017), Bitcoin has correlated with energy-related indices. Together with Litecoin, findings suggest Bitcoin and Litecoin as a portfolio has negative correlation relationship with some of the commodities and equities including energy and fuel-related commodities and MSCI China equity. Examining the coefficients like previous studies, Bitcoin within the portfolio, is very good at hedging against traditional assets, especially energy and fuel-related commodities. However, against to some of the previous studies such as Dyhrberg (2015) who shows Bitcoin could hedge against gold. Results from this study suggests neither Bitcoin nor Litecoin could be used to hedge against gold. Moreover, both cryptocurrencies are not good at hedging against exchange rates, whereas Dyhrberg (2015) suggests Bitcoin could hedge against US dollar in the short term. Although the evidence is mixed, Furthermore, this study fills in the gap by investigating whether Bitcoin and Litecoin could be a hedge against each other and form a hedge portfolio. Although some estimation results from VARX(1,0)-MGARCH(1,1)-DCC model suggests Bitcoin and Litecoin have a negative or little correlation. But by employing VAR(1)-MGARCH(1,1)-DCC model and constructing a portfolio using optimal weight portfolio methodology (Kroner and Ng, 1998). The results indicate the cryptocurrency portfolio is not good at hedging. Future work could be examining the hedging effectiveness of cryptocurrencies with traditional assets using other methodology or trying different formats of dated time series.

The above results suggest Bitcoin and Litecoin could not form a good portfolio for risk management. The finding favors to the conclusion that Bitcoin and Litecoin does not move in the opposite direction on average for the examined sample period. Future work could examine whether this is the case for different sample periods because the correlation between Bitcoin and Litecoin is likely to be time varying. Therefore there might be periods of time where the correlation is positive while other periods of time the correlation relationship becomes negative. Although this study does not suggest Bitcoin and Litecoin could form a good hedge portfolio. The same methodology could be used to apply to other cryptocurrencies and examine whether they could form a hedge portfolio. Moreoever, such a portfolio could extend to more than two cryptocurrencies. One of the implications of this study to cryptocurrency traders is that Bitcoin is dominating the cryptocurrency market. As a leader, its price movement has significant impact on other cryptocurrencies. Therefore, Litecoin price movement is following Bitcoin on average.

One of the limitation of this study is the frequency of the data. Only the week day data is used since the data collected from Datastream does not include the weekend data. In order to fill in the missing values, one could use the interpolation methods. It might also be worthy to examine the hedging effect using different data frequency such as weekly data does not have the missing weekend data problem.

4.8. Appendix

Defining variables
List of cryptocurrency returns variables:
lrb: Bitcoin return
lrl: Litecoin return

List of commodity returns variables:
comgeneral: S&P GSCI Commodity Spot return
comgold: S&P GSCI Gold Spot return
comimetal: S&P GSCI Industrial Metals Spot return
comagric: S&P GSCI Agriculture Spot return
compmetal: S&P GSCI Precious Metal Spot return
comenergy: S&P GSCI Energy Spot return
comoil: S&P GSCI Crude Oil Spot return
combio: S&P GSCI Biofuel Spot return
comgas: S&P GSCI Natural Gas Spot return

List of equity returns variables:
eqwor: MSCI WORLD return
eqeme: MSCI EMERGING return
eqacw: MSCI AC WORLD return
eqeur: MSCI EUROPE return
eqpac: MSCI PACIFIC return
equsa: MSCI USA return
eqjap: MSCI JAPAN return
eqchi: MSCI CHINA return

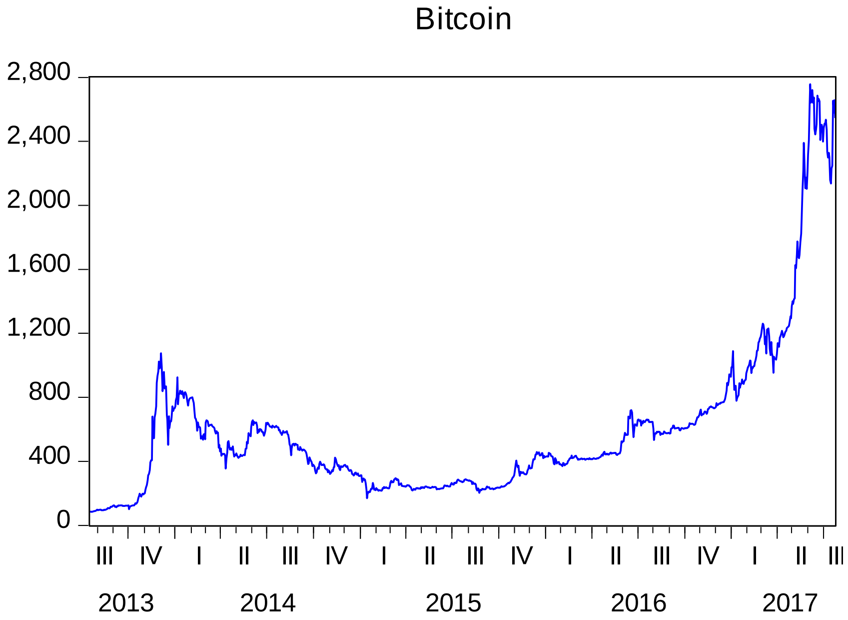
List of exchange rates returns variables:
Exjap:JAPANESE YEN/US DOLLAR return

Exchi:CHINESE YUAN/US DOLLAR return

Exaus: AUSTRALIAN DOLLAR/US DOLLAR return
Excan:CANADIAN DOLLAR/US DOLLAR return

Exuk: UK STERLING/US DOLLAR return
Exeur: EURO/US DOLLAR return

Exswi:SWISS FRANC/US DOLLAR return
Exind: INDIAN RUPEE/US DOLLAR return
Exafr: SOUTH AFRICA RAND/US DOLLAR return
Exbra: BRAZILIAN REAL/US DOLLAR return
Exusa: US DOLLAR INDEX return



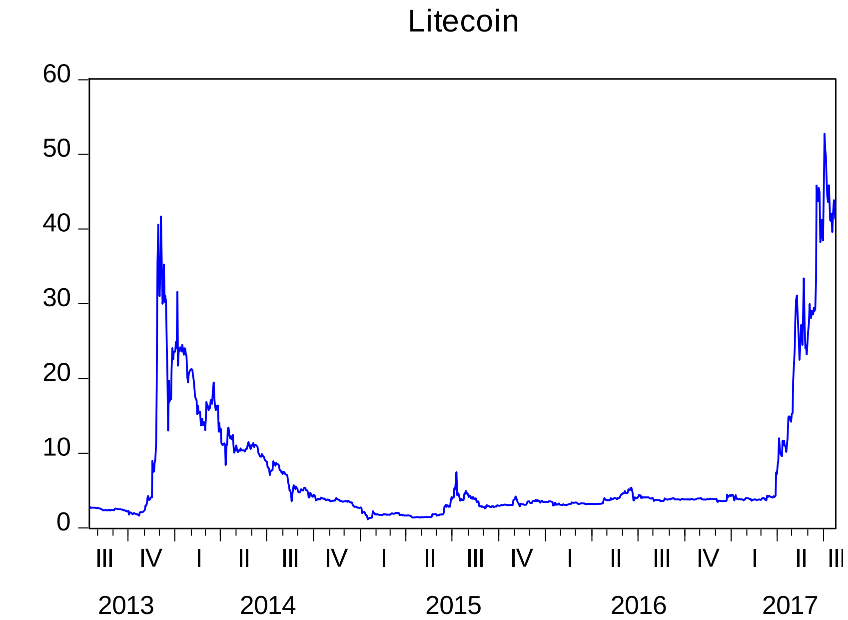


Diagram 1: Bitcoin and Litecoin price

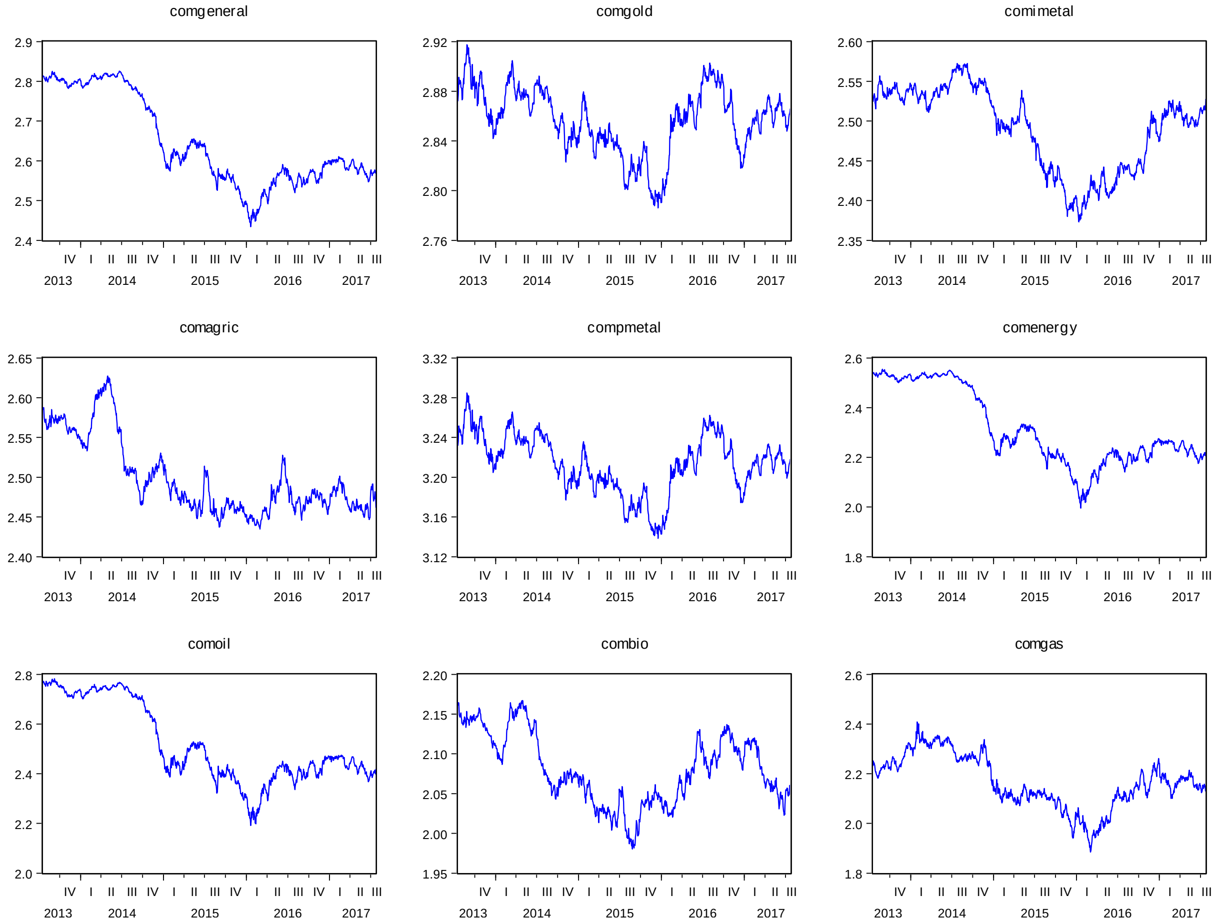


Diagram 2: S&P GSCI Commodity assets indices

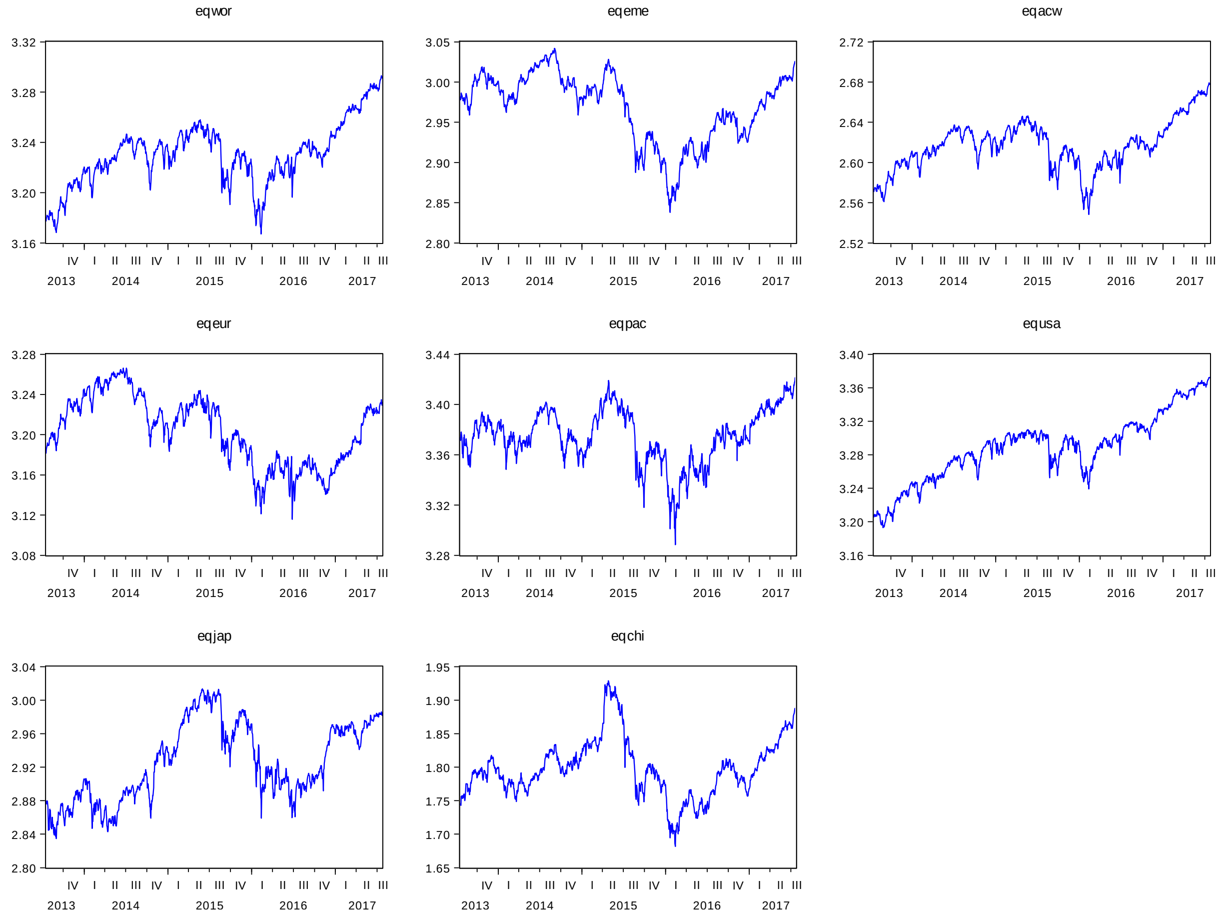


Diagram 3: MSCI Equity assets indices

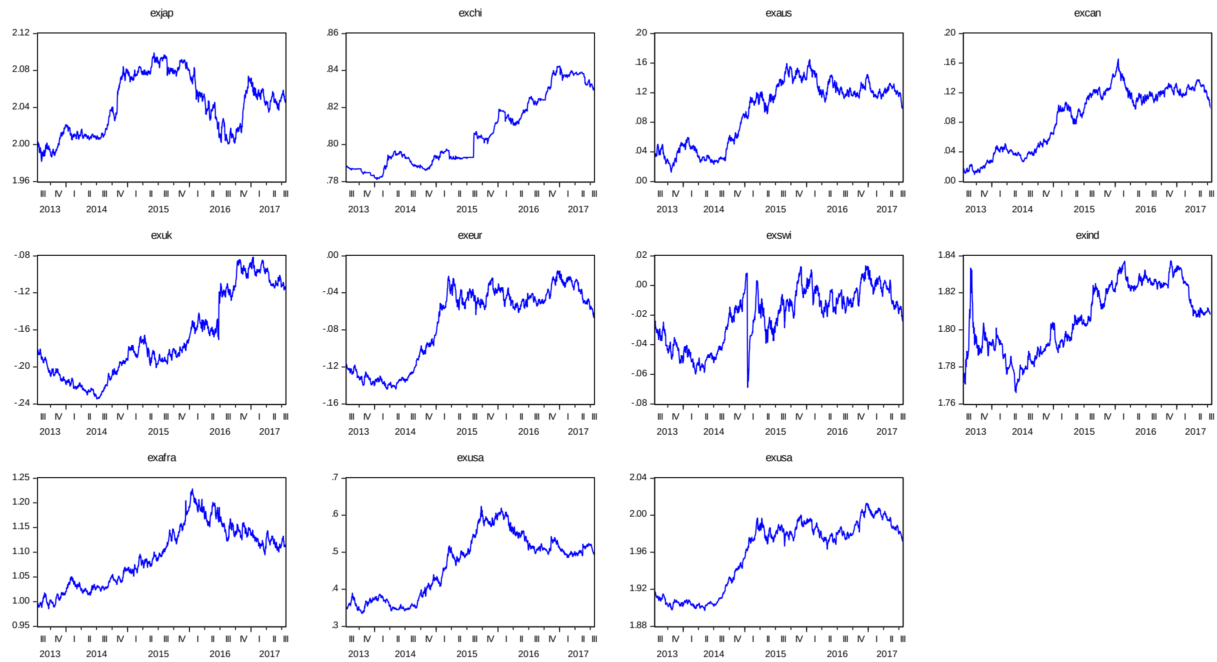
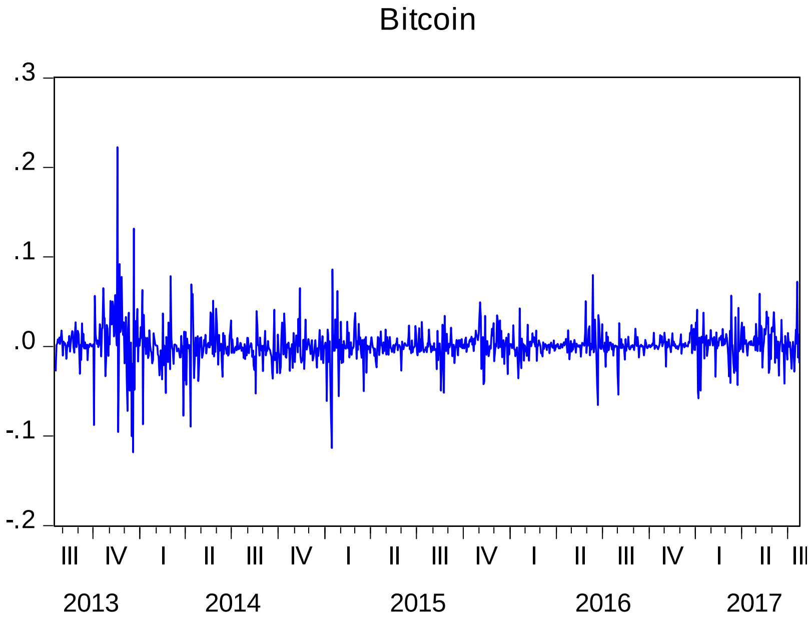


Diagram 4: Currency assets indices



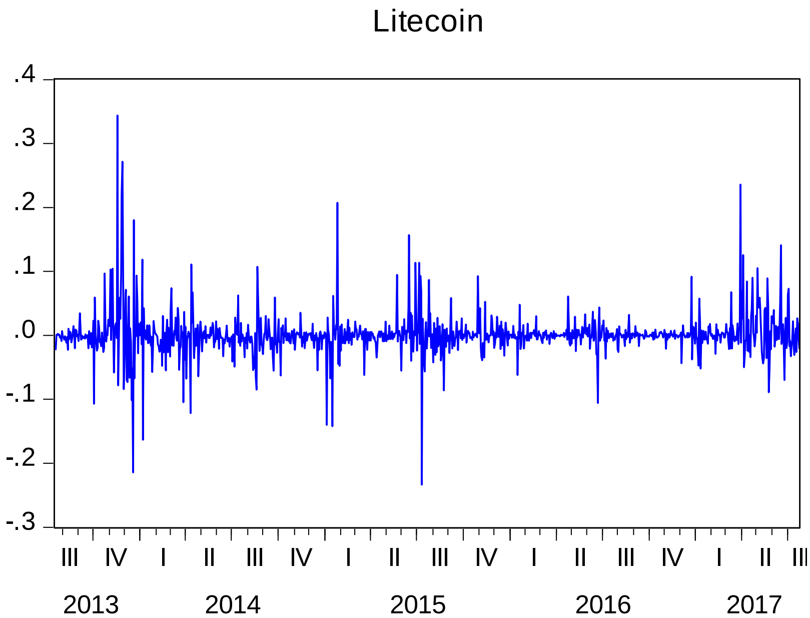


Diagram 5: Bitcoin and Litecoin returns

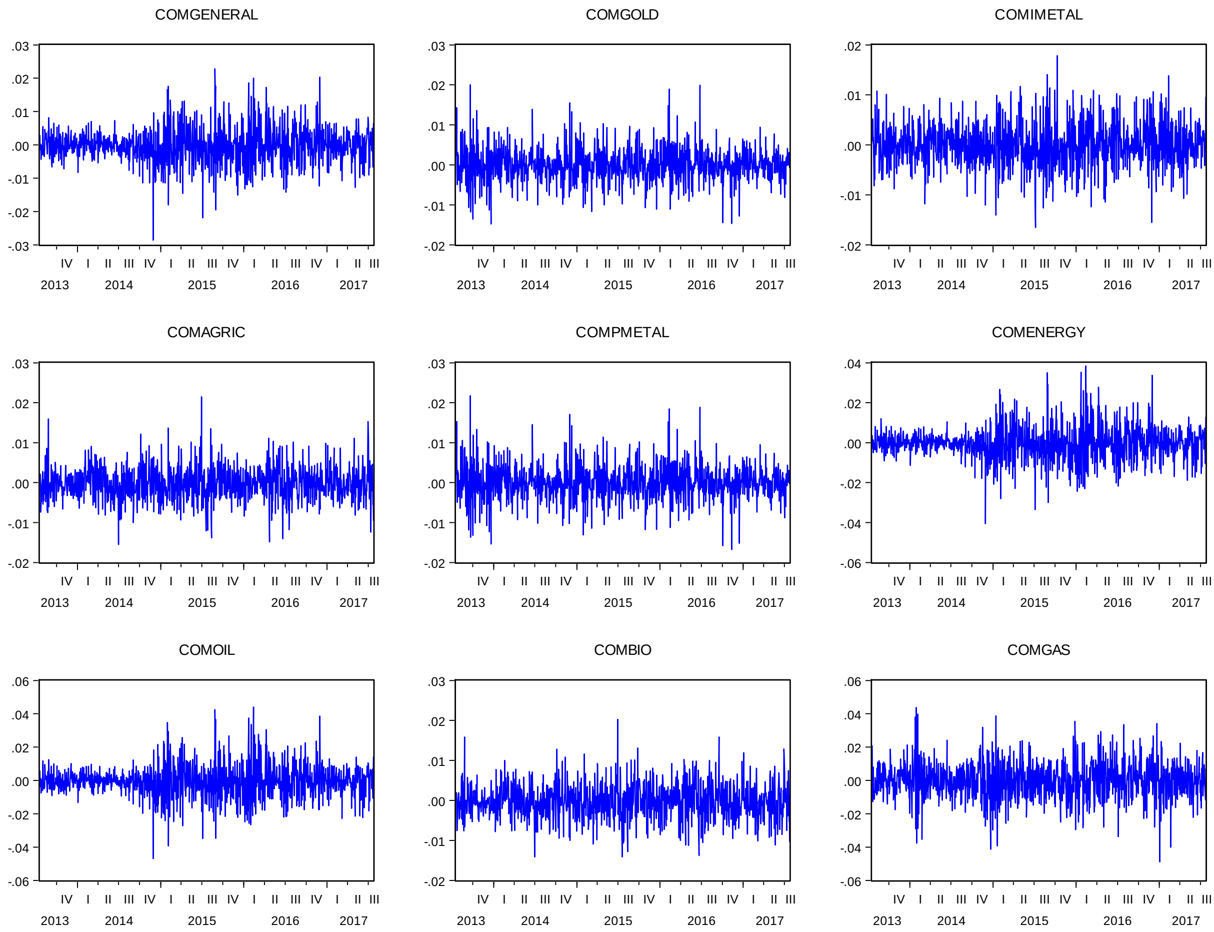


Diagram 6: S&P GSCI Commodity return indces

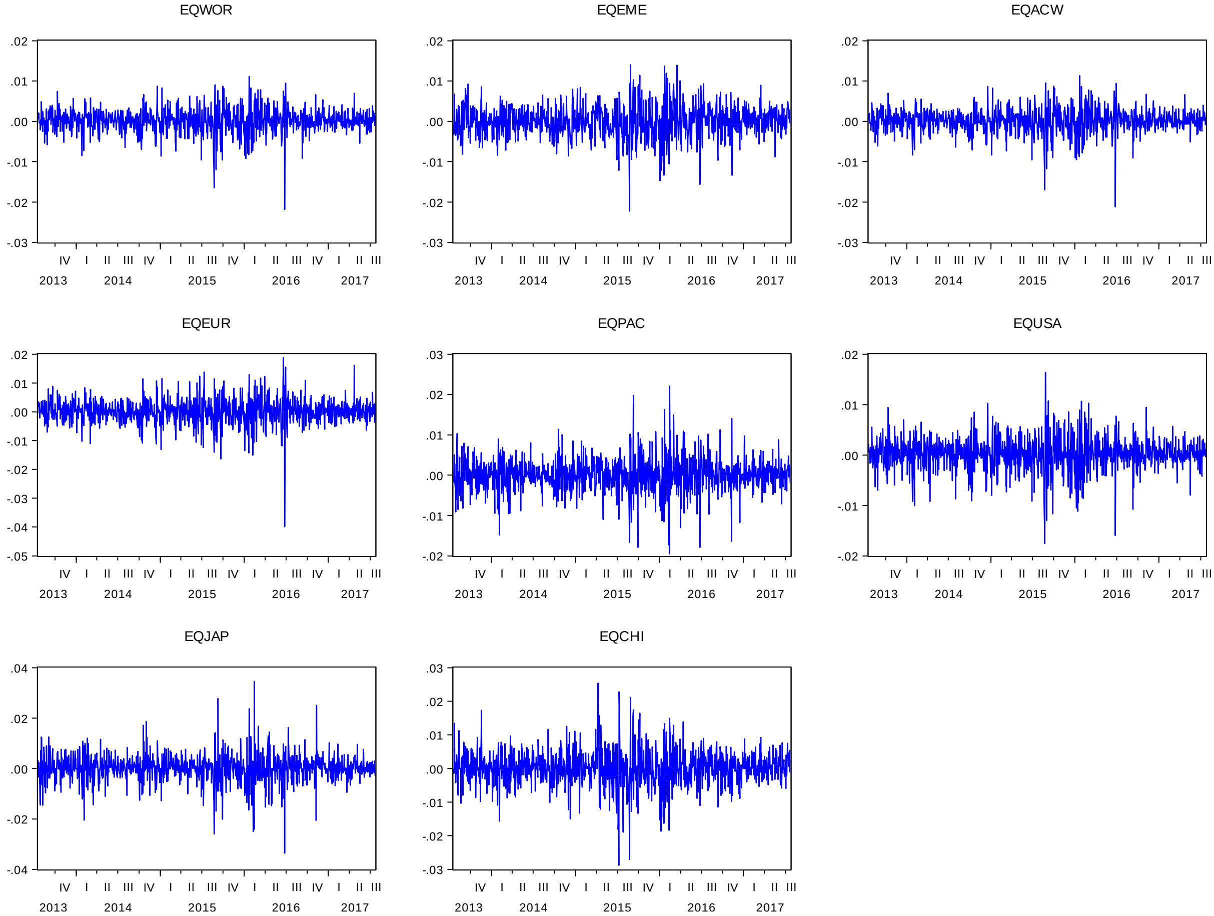


Diagram 7: MSCI Equity return indces

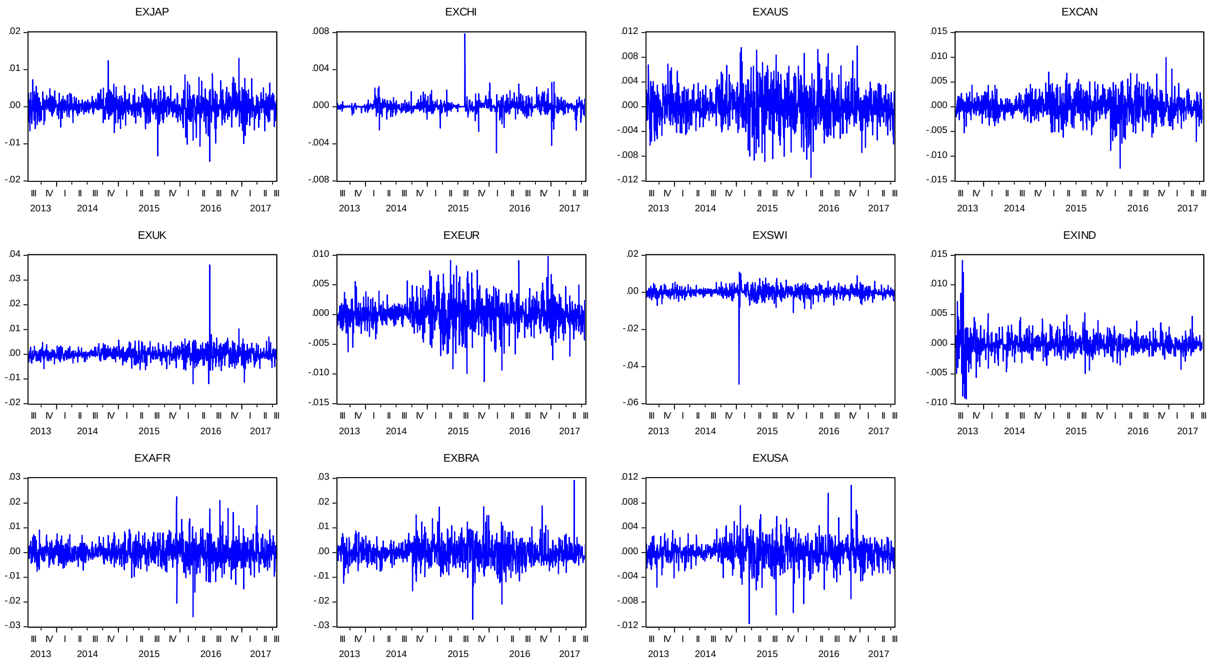


Diagram 8: Currency returns indices

Model 1.1.1	lrb_t	lrl_t
lrb_{t-1}	0.107*** 0.0000	0.422*** 0.000
lrl_{t-1}	-0.035*** 0.0000	-0.218*** 0.000
$comgeneral_{t-1}$	-1.440*** 0.000	-0.035 0.6949
$comgold_{t-1}$	-0.906*** 0.000	-1.487*** 0.000
$comimetal_{t-1}$	0.211*** 0.000	-0.145* 0.061
$comagric_{t-1}$	0.842*** 0.000	0.888*** 0.000
$compmetal_{t-1}$	0.977*** 0.000	1.661*** 0.000
$comenergy_{t-1}$	0.934*** 0.000	0.463*** 0.000
$comoil_{t-1}$	-0.0213 0.5356	-0.329*** 0.000
$combio_{t-1}$	-0.459*** 0.000	-0.638*** 0.000
$comgas_{t-1}$	-0.059* 0.0569	0.040 0.193

Table 1: Model 1.1.1: VARX(1,1)-DCC(1,1) with commodity return time series as exogenous variables

Model 1.1.2	lrb_t	lrl_t
lrb_{t-1}	No convergence	No convergence
lrl_{t-1}	No convergence	No convergence
$eqwor_{t-1}$	No convergence	No convergence
$eqeme_{t-1}$	No convergence	No convergence
$eqacw_{t-1}$	No convergence	No convergence
$eqeur_{t-1}$	No convergence	No convergence
$eqpac_{t-1}$	No convergence	No convergence
$equsa_{t-1}$	No convergence	No convergence
$eqjap_{t-1}$	No convergence	No convergence
$eqchi_{t-1}$	No convergence	No convergence

Table 2: Model 1.1.2: VARX(1,1)-DCC(1,1) with equity return time series as exogenous variables

Model 1.1.3	Lrb_t	Lrl_t
Lrb_{t-1}	0.105*** 0.000	0.436*** 0.000
Lrl_{t-1}	-0.027*** 0.000	-0.218*** 0.000
$exjap_{t-1}$	0.188* 0.068	0.345** 0.020
$exchi_{t-1}$	1.290** 0.012	1.029 0.133
$exaus_{t-1}$	0.455*** 0.000	0.417** 0.011
$excan_{t-1}$	-0.258** 0.050	-0.364** 0.047
$exuk_{t-1}$	0.071 0.574	0.271* 0.070
$exeur_{t-1}$	-0.355*** 0.004	-2.657*** 0.000
$exswi_{t-1}$	0.188 0.132	1.969*** 0.000
$exind_{t-1}$	-0.047 0.8029	-0.033 0.875
$exafr_{t-1}$	-0.107 0.1701	0.012 0.913
$exbra_{t-1}$	-0.039 0.5391	-0.259*** 0.002
$exusa_{t-1}$	0.202 0.2336	0.596*** 0.002

Table 3: Set 1.1.3: VARX(1,1)-DCC(1,1) with exchange rate return time series as exogenous variables

	Lrb_t	Lrl_t
Model 2.1.1		
lrb_{t-1}	0.010*** 0.00	0.426*** 0.00
lrl_{t-1}	-0.031*** 0.04	-0.214*** 0.00
$comgeneral_{t-1}$	0.1255** 0.0452	0.134 0.164
Model 2.1.2		
lrb_{t-1}	0.101*** 0.00	0.423*** 0.0000
lrl_{t-1}	-0.031*** 0.00	-0.214*** 0.0000
$comgold_{t-1}$	0.0526 0.345	0.176 0.1579
Model 2.1.3		
lrb_{t-1}	0.1009*** 0.000	0.430*** 0.000
lrl_{t-1}	-0.033*** 0.000	-0.221*** 0.000
$comimetal_{t-1}$	0.150** 0.025	-0.023 0.779
Model 2.1.4		
lrb_{t-1}	0.099*** 0.000	0.424*** 0.000
lrl_{t-1}	-0.030*** 0.000	-0.217*** 0.000
$comagric_{t-1}$	0.217*** 0.008	0.295*** 0.000
Model 2.1.5		
lrb_{t-1}	0.100*** 0.0000	0.423*** 0.0000
lrl_{t-1}	-0.030*** 0.0000	-0.214*** 0.0000
$compmetal_{t-1}$	0.074 0.178	0.185 0.108
Model 2.1.6		
lrb_{t-1}	0.099*** 0.0000	0.426*** 0.0000
lrl_{t-1}	-0.031*** 0.0000	-0.215*** 0.0000
$comenergy_{t-1}$	0.074* 0.0736	0.072 0.277
Model 2.1.7		
lrb_{t-1}	0.097*** 0.0000	0.425*** 0.0000

lrl $_{t-1}$	-0.031*** 0.0000	-0.215*** 0.000
comoil $_{t-1}$	0.061* 0.078	0.043 0.448
Model 2.1.8		
lrb $_{t-1}$	0.100*** 0.000	0.426*** 0.000
lrl $_{t-1}$	-0.031*** 0.000	-0.21*** 0.000
combio $_{t-1}$	0.030 0.700	0.039 0.6358
Model 2.1.9		
lrb $_{t-1}$	0.104*** 0.000	0.430*** 0.000
lrl $_{t-1}$	-0.032*** 0.000	-0.220*** 0.000
comgas $_{t-1}$	-0.065** 0.0435	0.020 0.564

Table 4: Set 2.1: VARX(1,1)-DCC(1,1) with single commodity return time series as exogenous variable

	Lrb_t	Lrl_t
Model 2.2.1		
lrb_{t-1}	0.101*** 0.00	0.432*** 0.00
lrl_{t-1}	-0.030*** 0.00	-0.216*** 0.00
$eqwor_{t-1}$	0.192 0.114	0.287** 0.032
Model 2.2.2		
lrb_{t-1}	0.104*** 0.00	0.427*** 0.00
lrl_{t-1}	-0.036*** 0.00	-0.220*** 0.00
$eqeme_{t-1}$	-0.184** 0.022	-0.185 0.177
Model 2.2.3		
lrb_{t-1}	0.101*** 0.00	0.429*** 0.00
lrl_{t-1}	-0.030*** 0.00	-0.215*** 0.00
$eqacw_{t-1}$	0.146 0.233	0.231 0.104
Model 2.2.4		
lrb_{t-1}	0.101*** 0.00	0.428*** 0.00
lrl_{t-1}	-0.032*** 0.00	-0.216*** 0.00
$eqeur_{t-1}$	0.0866 0.251	0.112 0.2325
Model 2.2.5		
lrb_{t-1}	0.105*** 0.00	0.427*** 0.00
lrl_{t-1}	-0.035*** 0.00	-0.219*** 0.00
$eqpac_{t-1}$	-0.188** 0.013	-0.027 0.8041
Model 2.2.6		
lrb_{t-1}	0.101*** 0.00	0.435*** 0.00
lrl_{t-1}	-0.030*** 0.00	-0.215*** 0.00
$equsa_{t-1}$	0.288*** 0.005	0.335*** 0.007
Model 2.2.7		
lrb_{t-1}	0.104*** 0.00	0.427*** 0.00

lrl $_{t-1}$	-0.033*** 0.00	-0.216*** 0.00
eqjap$_{t-1}$	-0.045 0.4783	0.076 0.3964
Model 2.2.8		
lrb $_{t-1}$	0.106*** 0.00	0.438*** 0.00
lrl $_{t-1}$	-0.039*** 0.00	-0.228*** 0.00
eqchi $_{t-1}$	-0.144*** 0.00	-0.280*** 0.00

Table 5: Set 2.2: VARX(1,1)-DCC(1,1) with single equity return time series as exogenous variable

	Lrb_t	Lrl_t
Model 2.3.1		
lrb_{t-1}	0.098*** 0.000	0.421*** 0.000
lrl_{t-1}	-0.030*** 0.000	-0.211*** 0.000
$exjap_{t-1}$	0.248** 0.026	0.393** 0.026
Model 2.3.2		
lrb_{t-1}	0.093*** 0.000	0.416*** 0.000
lrl_{t-1}	-0.031*** 0.000	-0.212*** 0.000
$exchi_{t-1}$	1.800*** 0.000	1.88*** 0.01
Model 2.3.3		
lrb_{t-1}	0.101*** 0.000	0.425*** 0.000
lrl_{t-1}	-0.030*** 0.000	-0.216*** 0.000
$exaus_{t-1}$	0.292*** 0.003	0.076 0.677
Model 2.3.4		
lrb_{t-1}	0.100*** 0.000	0.427*** 0.000
lrl_{t-1}	-0.032*** 0.000	-0.218*** 0.000
$excan_{t-1}$	0.033 0.808	-0.249 0.2505
Model 2.3.5		
lrb_{t-1}	0.101*** 0.000	0.424*** 0.000
lrl_{t-1}	-0.032*** 0.000	-0.213*** 0.000
$exuk_{t-1}$	0.174 0.1991	0.089 0.6321
Model 2.3.6		
lrb_{t-1}	0.101*** 0.000	0.430*** 0.000
lrl_{t-1}	-0.032*** 0.000	-0.217*** 0.000
$exeur_{t-1}$	0.197 0.1493	-0.139 0.4825
Model 2.3.7		
lrb_{t-1}	0.107*** 0.000	0.415*** 0.000

lrl_{t-1}	-0.028*** 0.000	-0.191*** 0.000
$exswi_{t-1}$	0.376*** 0.003	0.826*** 0.000
Model 2.3.8		
lrb_{t-1}	0.100*** 0.000	0.429*** 0.000
lrl_{t-1}	-0.033*** 0.000	-0.219*** 0.000
$exind_{t-1}$	0.193 0.2682	-0.047 0.8456
Model 2.3.9		
lrb_{t-1}	0.101*** 0.000	0.423*** 0.000
lrl_{t-1}	-0.032*** 0.000	-0.214*** 0.000
$exafr_{t-1}$	0.056 0.4790	-0.043 0.7160
Model 2.3.10		
lrb_{t-1}	0.101*** 0.000	0.419*** 0.000
lrl_{t-1}	-0.032*** 0.000	-0.213*** 0.000
$exbra_{t-1}$	0.006 0.9309	-0.234** 0.0130
Model 2.3.11		
lrb_{t-1}	0.098*** 0.000	0.406*** 0.000
lrl_{t-1}	-0.028*** 0.000	-0.200*** 0.000
$exusa_{t-1}$	0.453** 0.0135	0.705*** 0.0091

Table 6: Set 2.3: VARX(1,1)-DCC(1,1) with single exchange rate return time series as exogenous variable

Model 3.1.1.B		
	Lrb_t	$comgeneral_t$
Lrb_{t-1}	-0.010 0.661	-0.0004 0.936

comgeneral $_{t-1}$	0.132 0.118	-0.043 0.165
Model 3.1.2.B		
	Lrb_t	comimetal $_t$
Lrb_{t-1}	-0.016 0.491	0.0076 0.210
comimetal $_{t-1}$	0.1919** 0.012	-0.089*** 0.003
Model 3.1.3.B		
	Lrb_t	comagric $_t$
Lrb_{t-1}	-0.036 0.101	0.0009 0.898
comagric $_{t-1}$	0.309*** 0.001	0.046 0.111
Model 3.1.4.B		
	Lrb_t	comenergy $_t$
Lrb_{t-1}	-0.011 0.644	-0.002 0.745
comenergy $_{t-1}$	0.071 0.191	-0.049* 0.100
Model 3.1.5.B		
	Lrb_t	comoil $_t$
Lrb_{t-1}	-0.009 0.673	-0.005 0.599
comoil $_{t-1}$	0.064 0.183	-0.070** 0.025
Model 3.1.6.B		
	Lrb_t	comgas $_t$
lrb $_{t-1}$	-0.0012 0.956	-0.013 0.338
comgas $_{t-1}$	-0.059 0.143	-0.045 0.151
Model 3.1.7.B		
	lrl_t	comagric $_t$
lrl_t	No convergence	No convergence
comagric $_{t-1}$	No convergence	No convergence

Table 6: Set 3.1: Pairwise regression between cryptocurrency and commodity assets using VAR(1,1)-BEKK(1,1)

Model 3.2.1.B		
	Lrb_t	$eqeme_t$
Lrb_{t-1}	-0.0335 0.068	-0.002 0.607
$eqeme_{t-1}$	-0.060 0.590	0.228*** 0.000
Model 3.2.2.B		
	Lrb_t	$eqpac_t$
Lrb_{t-1}	-0.025 0.270	0.002 0.728
Lrb_{t-2}	-0.019 0.452	0.004 0.425
Lrb_{t-3}	-0.028 0.306	-0.001 0.850
Lrb_{t-4}	0.003 0.893	-0.003 0.615
$eqpac_{t-1}$	-0.191* 0.082	-0.088*** 0.001
$eqpac_{t-2}$	-0.084 0.442	-0.011 0.705
$eqpac_{t-3}$	-0.077 0.422	0.021 0.450
$eqpac_{t-4}$	0.033 0.723	-0.086*** 0.002
Model 3.2.3.B		
	Lrb_t	$equsa_t$
Lrb_{t-1}	-0.029 0.270	0.0109 0.001
$equsa_{t-1}$	0.161 0.197	-0.052* 0.086
Model 3.2.4.B		
	Lrb_t	$eqchi_t$
Lrb_{t-1}	-0.040** 0.020	-0.0005 0.925
$eqchi_{t-1}$	-0.0187 0.807	0.070** 0.011
Model 3.2.5.B		
	Lrl_t	$eqwor_t$
lrl_{t-1}	-0.028 0.236	0.0012 0.495
$eqwor_{t-1}$	0.083 0.720	0.106** 0.017

Model 3.2.6.B		
	Lrl_t	$equsa_t$
lrl_t	No convergence	No convergence
$equsa_{t-1}$	No convergence	No convergence
Model 3.2.7.B		
	Lrl_t	$eqchi_t$
lrl_{t-1}	-0.012 0.960	-0.003 0.538
lrl_{t-2}	-0.040 0.336	0.008** 0.081
$eqchi_{t-1}$	-0.329*** 0.002	0.063** 0.015
$eqchi_{t-2}$	0.261*** 0.009	-0.009* 0.09

Table 7: Set 3.2: Pairwise regression between cryptocurrency and equity assets using VAR(1,1)-BEKK(1,1)

Model 3.3.1.B		
	Lrb_t	exjap $_{t-1}$
Lrb_{t-1}	-0.008 0.726	0.0003 0.911
exjap $_{t-1}$	0.306** 0.031	0.022 0.485
Model 3.3.2.B		
	Lrb_t	exchi $_t$
Lrb_{t-1}	-0.020 0.393	0.0008 0.367
Lrb_{t-2}	-0.0238 0.369	-0.001 0.3378
Lrb_{t-3}	-0.0438 0.147	-0.002 0.160
exchi $_{t-1}$	1.094** 0.028	0.084*** 0.006
exchi $_{t-2}$	-0.756 0.349	-0.058* 0.070
exchi $_{t-3}$	0.324 0.605	0.070** 0.040
Model 3.3.3.B		
	Lrb_t	exaus $_t$
Lrb_{t-1}	No convergence	No convergence
exaus $_{t-1}$	No convergence	No convergence
Model 3.3.4.B		
	Lrb_t	exswi $_t$
Lrb_{t-1}	No convergence	No convergence
Lrb_{t-2}	No convergence	No convergence
Lrb_{t-3}	No convergence	No convergence
Lrb_{t-4}	No convergence	No convergence
Lrb_{t-5}	No convergence	No convergence
Lrb_{t-6}	No convergence	No convergence
Lrb_{t-7}	No convergence	No convergence
exswi $_{t-1}$	No convergence	No convergence
exswi $_{t-2}$	No convergence	No convergence
exswi $_{t-3}$	No convergence	No convergence
exswi $_{t-4}$	No convergence	No convergence
exswi $_{t-5}$	No convergence	No convergence
exswi $_{t-6}$	No convergence	No convergence
exswi $_{t-7}$	No convergence	No convergence
Model 3.3.5.B		
	Lrb_t	exusa $_t$

Lrb_{t-1}	-0.008 0.724	-0.001 0.606
$exusa_{t-1}$	0.2473 0.291	0.0776*** 0.007
Model 3.3.6.B		
	Lrl_t	$exjap_t$
lrl_t	-0.013 0.590	0.002 0.512
$exjap_{t-1}$	0.326** 0.023	0.016 0.586
Model 3.3.7.B		
	Lrl_t	$exchi_t$
lrl_{t-1}	-0.020 0.277	0.0007 0.424
$exchi_{t-1}$	1.010** 0.044	0.076** 0.015
Model 3.3.8.B		
	Lrl_t	$exswi_t$
lrl_{t-1}	-0.063*** 0.002	0.004* 0.084
lrl_{t-2}	0.019 0.524	0.003 0.412
lrl_{t-3}	-0.030 0.319	-0.002 0.537
lrl_{t-4}	0.015 0.584	-0.005 0.201
lrl_{t-5}	0.030 0.288	-0.004 0.387
lrl_{t-6}	-0.022 0.449	-0.004 0.325
lrl_{t-7}	-0.073** 0.013	0.006* 0.063
$exswi_{t-1}$	0.0902 0.647	-0.034 0.287
$exswi_{t-2}$	0.151 0.409	0.034 0.288
$exswi_{t-3}$	-0.325* 0.10	0.028 0.216
$exswi_{t-4}$	-0.190 0.279	0.019 0.356
$exswi_{t-5}$	0.137 0.458	-0.053** 0.044
$exswi_{t-6}$	-0.266*	-0.027

	0.06	0.270
exswi $_{t-7}$	0.0018 0.994	-0.117*** 0.000
Model 3.3.9.B		
	Lrl_t	exbra $_t$
lrl_t	No convergence	No convergence
exbra $_{t-1}$	No convergence	No convergence
Model 3.3.10.B		
	Lrl_t	exusa $_t$
lrl_t	No convergence	No convergence
exusa $_{t-1}$	No convergence	No convergence

Table 8: Set 3.3: Pairwise regression between cryptocurrency and currency assets using VAR(1,1)-BEKK(1,1)

Model 3.1.1.D		
	Lrb_t	$comgeneral_t$
Lrb_{t-1}	No convergence	No convergence
$comgeneral_{t-1}$	No convergence	No convergence
Model 3.1.2.D		
	Lrb_t	$comimetal_t$
Lrb_{t-1}	-0.0003 0.990	0.007 0.210
$comimetal_{t-1}$	0.168** 0.040	-0.085*** 0.005
Model 3.1.3.D		
	Lrb_t	$comagric_t$
Lrb_{t-1}	-0.011 0.654	0.005 0.420
$comagric_{t-1}$	0.237*** 0.008	0.054* 0.085
Model 3.1.4.D		
	Lrb_t	$comenergy_t$
Lrb_{t-1}	-0.009 0.717	-0.002 0.815
$comenergy_{t-1}$	0.071 0.191	-0.049 0.142
Model 3.1.5.D		
	Lrb_t	$comoil_t$
Lrb_{t-1}	-0.008 0.739	-0.005 0.599
$comoil_{t-1}$	0.064 0.171	-0.072** 0.034
Model 3.1.6.D		
	Lrb_t	$comgas_t$
lrb_{t-1}	No convergence	No convergence
$comgas_{t-1}$	No convergence	No convergence
Model 3.1.7.D		
	lrl_t	$comagric_t$
lrl_t	No convergence	No convergence
$comagric_{t-1}$	No convergence	No convergence

Table 9: Set 4.1: Pairwise regression between cryptocurrency and commodity assets using VAR(1,1)-DCC(1,1)

Model 3.2.1.D		
	Lrb_t	eqeme $_t$
Lrb_{t-1}	-0.007 0.761	0.0005 0.924
eqeme $_{t-1}$	-0.079 0.479	0.229*** 0.000
Model 3.2.2.D		
	Lrb_t	eqpac $_t$
Lrb_{t-1}	No convergence	No convergence
Lrb_{t-2}	No convergence	No convergence
Lrb_{t-3}	No convergence	No convergence
Lrb_{t-4}	No convergence	No convergence
eqpac $_{t-1}$	No convergence	No convergence
eqpac $_{t-2}$	No convergence	No convergence
eqpac $_{t-3}$	No convergence	No convergence
eqpac $_{t-4}$	No convergence	No convergence
Model 3.2.3.D		
	Lrb_t	$equsa_t$
Lrb_{t-1}	No convergence	No convergence
$equsa_{t-1}$	No convergence	No convergence
Model 3.2.4.D		
	Lrb_t	eqchi $_t$
Lrb_{t-1}	-0.011 0.638	0.003 0.619
eqchi $_{t-1}$	-0.037 0.647	0.076** 0.023
Model 3.2.5.D		
	Lrl_t	eqwor $_t$
lrl_{t-1}	-0.005 0.855	0.001 0.562
eqwor $_{t-1}$	0.164 0.441	0.108*** 0.001
Model 3.2.6.D		
	Lrl_t	$equsa_t$
lrl_t	No convergence	No convergence
$equsa_{t-1}$	No convergence	No convergence
Model 3.2.7.D		
	Lrl_t	eqchi $_t$
lrl_{t-1}	-0.012 0.661	-0.002 0.707

lrl_{t-2}	-0.026 0.492	0.009** 0.049
$eqchi_{t-1}$	-0.325*** 0.002	0.077** 0.018
$eqchi_{t-2}$	0.251** 0.012	-0.008 0.795

Table 10: Set 4.2: Pairwise regression between cryptocurrency and commodity assets using VAR(1,1)-DCC(1,1)

Model 3.3.1.D		
	Lrb_t	$exjap_{t-1}$
Lrb_{t-1}	-0.010 0.6813	0.00005 0.9856
$exjap_{t-1}$	0.2907** 0.0387	0.0221 0.4956
Model 3.3.2.D		
	Lrb_t	$exchi_t$
Lrb_{t-1}	No convergence	No convergence
Lrb_{t-2}	No convergence	No convergence
Lrb_{t-3}	No convergence	No convergence
$exchi_{t-1}$	No convergence	No convergence
$exchi_{t-2}$	No convergence	No convergence
$exchi_{t-3}$	No convergence	No convergence
Model 3.3.3.D		
	Lrb_t	$exaus_t$
Lrb_{t-1}	No convergence	No convergence
$exaus_{t-1}$	No convergence	No convergence
Model 3.3.4.D		
	Lrb_t	$exswi_t$
Lrb_{t-1}	No convergence	No convergence
Lrb_{t-2}	No convergence	No convergence
Lrb_{t-3}	No convergence	No convergence
Lrb_{t-4}	No convergence	No convergence
Lrb_{t-5}	No convergence	No convergence
Lrb_{t-6}	No convergence	No convergence
Lrb_{t-7}	No convergence	No convergence
$exswi_{t-1}$	No convergence	No convergence
$exswi_{t-2}$	No convergence	No convergence
$exswi_{t-3}$	No convergence	No convergence
$exswi_{t-4}$	No convergence	No convergence
$exswi_{t-5}$	No convergence	No convergence
$exswi_{t-6}$	No convergence	No convergence
$exswi_{t-7}$	No convergence	No convergence

Model 3.3.5.D		
	Lrb_t	exusa $_t$
Lrb_{t-1}	-0.008 0.724	-0.001 0.606
exusa $_{t-1}$	0.2473 0.291	0.0776*** 0.007
Model 3.3.6.D		
	Lrl_t	exjap $_t$
lrl_t	No convergence	No convergence
exjap $_{t-1}$	No convergence	No convergence
Model 3.3.7.D		
	Lrl_t	exchi $_t$
lrl_{t-1}	-0.007 0.772	0.00009 0.890
exchi $_{t-1}$	2.003* 0.077	0.100*** 0.008
Model 3.3.8.D		
	Lrl_t	exswi $_t$
lrl_{t-1}	No convergence	No convergence
lrl_{t-2}	No convergence	No convergence
lrl_{t-3}	No convergence	No convergence
lrl_{t-4}	No convergence	No convergence
lrl_{t-5}	No convergence	No convergence
lrl_{t-6}	No convergence	No convergence
lrl_{t-7}	No convergence	No convergence
exswi $_{t-1}$	No convergence	No convergence
exswi $_{t-2}$	No convergence	No convergence
exswi $_{t-3}$	No convergence	No convergence
exswi $_{t-4}$	No convergence	No convergence
exswi $_{t-5}$	No convergence	No convergence
exswi $_{t-6}$	No convergence	No convergence
exswi $_{t-7}$	No convergence	No convergence
Model 3.3.9.D		
	Lrl_t	exbra $_t$
lrl_t	No convergence	No convergence
exbra $_{t-1}$	No convergence	No convergence
Model 3.3.10.D		
	Lrl_t	exusa $_t$
lrl_t	No convergence	No convergence

Table 11: Set 4.3: Pairwise regression between cryptocurrency and commodity assets using VAR(1,1)-DCC(1,1)

Chapter 5

Conclusion and implication

In 2009, Satoshi created the first cryptocurrency which solves the double spending problem without the existence of any third parties using the block-chain technology. Based on the block-chain technology, many applications could be built to form different kinds of decentralized platforms. Each of these platform have their own cryptocurrencies in order to motivate miners to maintain the platform. If the platform is large in terms of capitalization, then the platform is more decentralized. The first block-chain application is the money application, cryptocurrencies such as Bitcoin and Litecoin were created to replace the traditional payment system. This thesis mainly considers the money application type of cryptocurrencies because majority of the largest cryptocurrencies serve as a payment system with different features. This thesis is divided in four chapters. The first chapter describes the mechanism of bitcoin network. The second chapter investigates whether Bitcoin market is efficient by examining the price return predictability in the short run and whether there exist arbitrage opportunity among different exchange markets. The third chapter investigates the dynamic relationship between Bitcoin and Litecoin market and focus on the volatility transmission between two cryptocurrency markets. The fourth chapter investigates whether Bitcoin and Litecoin have hedging or diversifying ability against traditional financial assets such as commodity, stock and exchange rates.

Chapter 2

Cryptocurrency market is new compare to other traditional financial markets. It has many exchange markets around the world which could be traded using different fiat currency 24 hours a day and 7 days a week. Many of the existing literature test the traditional financial market efficiency by using closing price to calculate the return. However, since Bitcoin could be traded globally and continuously, the closing price does not have significant meaning as it does for the traditional financial market. The average price would not be accurate to calculate the return either because the Bitcoin price is volatile which has greater price range. Such price range might have useful information. According to the weak form of market efficiency hypothesis, the Bitcoin price should reflect all the historical information and the past information is not helpful in predicting the current or future price movement. In this sense, the open, high, low and close price represent the price at that particular moment only. If Bitcoin market is efficient, then the historical data for these intra-day data should not provide any information for the future price movement.

In this chapter, I focus on the price behaviour for different types of intra-day data. Moreover, given the nature of the trading exchange market where cryptocurrencies could be traded continuously globally and Bitcoin price is volatile compare to most financial assets. We apply the Yang-zhang historical volatility estimator using open, high, low and close intraday data to examine whether the volatility in the past could predict the future Bitcoin price movement. In addition, arbitrage opportunity among different exchange markets are examined.

Findings suggest the past close price return cannot predict its current return. The only current price return that could be predicted by its own lag is the high price return. Moreover, there exist another cryptocurrency, Litecoin, whose past return is significant in predicting the current return of Bitcoin. Moreover, the historical yang-zhang volatility estimator is useful in predicting both Bitcoin current return and the conditional current volatility.

In terms of arbitrage opportunity, results indicate arbitrage opportunity does not exist between Bitfinex and OkCoin exchange market. Supporting the previous section that the use of close price returns could reject the efficient market hypothesis. In addition, the use of intra-day extreme data allows seeking for arbitrage opportunity which violates the efficient market hypothesis.

Chapter 3

From the third chapter, we found some evidence suggesting the historical information can provide useful information in predicting the future price movement for Bitcoin. However, this only happens in a very short period. It is difficult for cryptocurrency traders to make profit unless long term pattern could be found for the cryptocurrency market. This is what motivates me to find whether there exist long run relationship between Bitcoin and Litecoin by investigating their long run covariance.

Bitcoin is the first cryptocurrency, although Bitcoin has the largest capitalization in the cryptocurrency market, but its technology is old. Therefore in the third chapter, I'm also interested in examining the relationship between Bitcoin and another cryptocurrency Litecoin in both short run and long run. The reason for choosing Litecoin is that, it is also a payment system like Bitcoin which could be traded globally using the block-chain technology. But Litecoin uses different mining algorithm called Scrypt instead of SHA256 which is more efficient in mining. In addition, Litecoin can handle more transaction than Bitcoin per second. (Bitcoin can handle 7 transaction per second while Litecoin can handle 56 transaction per second). If evidence suggests Litecoin could compete with Bitcoin, then it is reasonable to expect Bitcoin is only worth of investing until other cryptocurrencies with better feature are being created. In another word, Bitcoin could be replaced in the future although it is the first cryptocurrency. To the best of my knowledge, none of the existing study examine the volatility transmission between two different cryptocurrency markets. Some similar studies investigate the relationship between Bitcoin and other traditional financial market. However, this does not provide any useful interpretation because the size of Bitcoin market is still very small compare to stock, bond, commodity or exchange markets. Therefore, the volatility transmission only make sense from traditional financial market to Bitcoin market. In the second chapter, we examine two comparative cryptocurrency markets and examine whether the covariance is stable in the long run between two markets. Moreover, we include some exogenous variables in both conditional mean equations to further explore the relationship between two markets. This is the first study to examine the whether Bitcoin and Litecoin markets have an impact on each other by considering variables other than price return and volatility.

Results suggest transaction volume and growth rate of hashrates of one cryptocurrency have different degrees of impacts between Bitcoin and Litecoin. Litecoin, being a follower of Bitcoin in cryptocurrency market, moves in the same direction as Bitcoin on average. This implies a diversified portfolio might be constructed. Moreover, diversification is not only about correlation. Parts of the findings suggest Litecoin exhibit some new feature when compare to Bitcoin which brings positive impact on Litecoin return. This implies people like holding cryptocurrency with better features. Bitcoin being the first cryptocurrency might only have the fundamental feature. Different features of Litecoin as cryptocurrency might be able to reduce another type of risks. Therefore, a diversified portfolio containing Bitcoin and Litecoin could be constructed in order to reduce the level of risk. Such implication is useful for an investor who wants to include cryptocurrency in their portfolio but is concerned about the risk.

One of the limitation of this chapter is that the covariance between Bitcoin and Litecoin volatility is not stable in the long run when using BEKK model. This problem could be addressed by considering structural break and consider different sub-sample periods. The same methodology could be applied to more than two cryptocurrencies and examine the dynamic relationship among them.

Chapter 4

From the third chapter, we found there exist volatility transmission between Bitcoin and Litecoin markets. However, the covariance is not stable in the long run for the examined sample period. Therefore, it might be a good idea to consider structural break or split the whole sample period into two sub-sample period. In the fourth chapter, the dynamic correlation covariance method is employed rather than BEKK methodology for the conditional variance covariance model. The motivation is to further examine the relationship between Bitcoin and Litecoin as well as exploring the hedging and diversifying property of these two cryptocurrencies against traditional financial assets. If evidence suggest cryptocurrencies could hedge against traditional financial assets on average, then further study can carry out and examine whether the long run relationship between cryptocurrency and other financial assets could be found. If both long run relationship and hedging property could be found, then cryptocurrency could be included in an investment portfolio in order to reduce the risk. Existing literature examine the hedging or diversifying ability of Bitcoin by examining the correlation between two assets on average. The contribution of this chapter is that we include a third asset into consideration and examine the triangular relationship before concluding whether Bitcoin or Litecoin act as hedge or diversifier against traditional financial assets.

Results suggest both Bitcoin and Litecoin could hedge against traditional assets. In line with previous study from Bouri et al., (2016), Bitcoin is negatively correlated with Chinese stock where Bouri uses weekly data. Bitcoin does not correlate with Japanes stock and MSCI pacific where Bouri uses daily data. This evidence suggest the same findings even different frequency of data is used. Moreover, in line with Bouri et al., (2017), Bitcoin has correlated with energy-related indices. Together with Litecoin, findings suggest Bitcoin and Litecoin as a portfolio has negative correlation relationship with some of the commodities and equities including energy and fuel-related commodities and MSCI China equity. Examining the coefficients like previous studies, Bitcoin within the portfolio, is very good at hedging against traditional assets, especially energy and fuel-related commodities. However, against to some of the previous studies such as Dyhrberg (2015) who shows Bitcoin could hedge against gold. Results from this study suggests neither Bitcoin nor Litecoin could be used to hedge against gold. Moreover, both cryptocurrencies are not good at hedging against exchange rates, whereas Dyhrberg (2015) suggests Bitcoin could hedge against US dollar in the short term. Although the evidence is mixed,

The results suggest Bitcoin and Litecoin could not form a good portfolio for risk management. The finding favors to the conclusion that Bitcoin and Litecoin does not move in the opposite direction on average for the examined sample period. Future work could examine whether this is the case for different sample periods because the correlation between Bitcoin and Litecoin is likely to be time varying. Therefore there might be periods of time where the correlation is positive while other periods of time the correlation relationship becomes negative. Although this study does not suggest Bitcoin and Litecoin could form a good hedge portfolio. The same methodology could be used to apply to other cryptocurrencies and examine whether they could form a hedge portfolio. Moreover, such a portfolio could extend to more than two cryptocurrencies. One of the implications of this study to cryptocurrency traders is that Bitcoin is dominating the cryptocurrency market. As a leader, its price movement has significant impact on other cryptocurrencies. Therefore, Litecoin price movement is following Bitcoin on average. Based on the findings discussed above, this thesis suggests the price movements of cryptocurrencies behave more like financial assets instead of currencies. Cryptocurrency traders should consider Bitcoin as a bench mark. Including other cryptocurrencies in a portfolio might not reduce risk as they will be more volatile due to small capitalization.

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